Computer-Based Intelligence Methods Applied for Personalized Management of Diabetes

Matthias Reuter and Sabine Bohlmann

Abstract Type 2 diabetes has become a typical civilization disease in which modern lifestyle changes are recognized risk factors. Currently, diabetes management is one of the important areas of therapeutic and social medical care. In this paper, we present a computer-intelligence based system for diabetes management and patient trend analysis, which is based on data from a set of questionnaires. Questionnaires are proven tools to handle, evaluate and improve the diabetes management of patients and their acceptance of the disease. Our system was developed based on a large range of questionnaires from American and German diabetes patients. We used the data sets to train a new kind of neural net to create personal fingerprints, enable an individual therapeutic support, and guarantee continuous monitoring over time. Our categorizers differ especially between social, educational and ethnic background and are based on a class-oriented four level statistic. The states of patients' factoring differ between psychological, physiological, familiar and social factors. These have very important influence on the management of type 2 diabetes and the success of therapy as well as the acceptance of the disease itself. Due to its structure, the system can be continuously adapted and sensitized by means of new data. In that way, over time, regional influences are incorporated automatically into the system's categorization and behaviour. In this way, our system leads to a supervision and guidance system for patients and the attending physicians and guarantees at least an overall cost reduction.

Keywords Diabetes · Computing With Activities (CWA) · Personal diabetes management

M. Reuter · S. Bohlmann (✉)
Department of Big Data and Technical Information Systems, TU Clausthal - Institute for Informatics/IngB RT&S, Clausthal-Zellerfeld, Germany
e-mail: sabine.bohlmann@tu-clausthal.de

M. Israelowitz et al. (eds.), *Biomimetics and Bionic Applications with Clinical Applications*, Series in BioEngineering,
https://doi.org/10.1007/978-3-319-53214-1_13

1 Introduction

Diabetes (diabetes mellitus) describes a group of metabolic diseases in which a person has high blood glucose, either because insulin production is inadequate, or because the body's cells do not respond properly to insulin, or both. Diabetes can be classified in two forms: Diabetes Type 1 and Diabetes Type 2 [1, 2].

In type 1 Diabetes there is inability to produce insulin (insulin-dependent diabetes, juvenile diabetes, or early-onset diabetes). Usually this type develops before their 40th year, often in early adulthood or teenage years. Approximately 10% of all diabetes cases are type I. In type 2 diabetes, there is either inadequate production of insulin for proper function or the cells in the body do not react to insulin (insulin resistance). Approximately 90% of all cases of diabetes worldwide are type 2. Sometimes Type 2 diabetes symptoms can be controlled by losing weight, following a healthy diet, doing a lot of exercise, with appropriate monitoring of blood glucose levels. However, Type 2 diabetes is typically a progressive disease and patients will probably end up have to syringe insulin [1, 2]. As both forms differ, every diabetes management system has to distinguish both groups generally, economically, and socio-culturally [3, 4]. The degree of complexity required means that Common expert systems or simpler software may be unable to handle required parameters in the context of an individual finger print of patient's behaviour and disease patterns.

In the last few years, Computer-based Intelligence (CI) has enabled scientists and other stakeholders in medicine and industry to categorize or diffuse uncompleted data by self-learning and in a hyperspace acting algorithm. Together with an adequate encoding, this knowledge enables one to create personal fingerprint software for disease management and to handle diverse data in the context of Big Data [5–7]. In line with this, in the last few years, we developed and tested a special software tool for personalized management of diabetes. Based on a large range of questionnaires from USA and Germany, we trained special neural nets to create a personal fingerprint of different patients (and their medical histories), to form a global categorizer for new patients and/or cohorts of patients with different social, educational and ethnic backgrounds. Furthermore, based on a class oriented four level statistic, we can show, that special analysis of different aspects like psychological, physiological, familiar and social estimates leads to a supervision and guidance system for patients and the attending physicians. That these aspects are import end for a 360° view on the patient was shown in many other scientific, medical-orientated researches [8–16]. The system involves the use of an on-line data bank as well as highly dimensioned questionnaires. The patients answer different questions at their convenience and to the degree to which they are empowered to answer or if the momentary status of a patient being analyzed fit a trend of analysis.

2 Methods

2.1 Basic Modules of the System

Our personal diabetes management system consists of four different modules:

- Data Bank Module (DB), storing all questionnaires and the answers to them, personal data, trends, neural net structures and labels for the different country versions.
- Online and Printing Module (OPM), enabling the connection to the World Wide Web, the email sending/receipt, the report generation and the communication to the printer equipment of the physician's office.
- The Graphical User Interface Software (GUI), enabling the Man-Machine-Interaction (Patient to Computer Dialog, PCD), the help functions and the choice of the language based labeling of the system.
- The CI-Module, involving the neural net structures, the special categorization algorithm, the learning procedures for the system and the evaluation and visualization modules for testing on confidence.

The system itself has four working Modes:

- Patients Mode (PM)
- Doctors Mode (DM)
- Maintenance Mode (MM)
- Condition Mode (CM).

These modes are protected separately by special Personal Identification Number (PIN)-Codes for data security.

2.2 Basic Functionalities of the System

To ensure data security, for every patient and the doctor's office information, there is a 6-letter password that enables the different users to see all personal data, the results of all questionnaires and trend analysis results. Furthermore, the doctor's office function is able to create new patient's "cards", which means new patient profiles stored in the data bank.

If a new patient profile is created, in the first step, all necessary personal data is evaluated by an interactive PCD-dispute, whereby the systems check all data on logic and completeness. In the second step, the patient is lead through the questionnaire. In our system, this questionnaire is divided in 10 logical categories to analyse different items of patient's life and behaviour such as:

- disease status and disease history
- physical status
- psychological status

– social status
– family status
– status of cooperation
– self-assessment
– foreign assessment
– combination of all items listed before for cross-checking.

After the patient has answered all questions, (optional ones in some categories) the system will categorize the patient via its neural structure. These categorization results can be sent to the doctor's office and/or the patient on demand, via internet and/or mobile devices, whereby the results are bundled in a pdf-report.

In the doctor's mode the system can be conditioned, which means special neural nets can be created and trained. Furthermore, the doctor is able to create a statistical and neural overview from all the patient data.

2.3 Principle of the Neural Net Based Categorizer

The core of the system can be found in the neural net structure, which is the underlying data analysis algorithm of a personal diabetes management system. Here we explain some of the basis of these CI-oriented methods. Neural nets are more or less nothing more than a simulation algorithm of central nervous functionalities [17–19]. Therefore, they can be divided in several neurons, which are combined via synaptic connection, whereby these connections can be conditioned in a special training modus. The training itself can be done in two modes, supervised and unsupervised. Supervised training can be done easily if one knows everything about the system to be categorized or examples of all possible states of the system are known. In our case, as we don't know from the beginning how many different classes of patient or (different) states of the disease are existent, this method is not sufficient for a managing system.

The second method to train a network, the unsupervised training, for us, is sufficient as the training algorithm divides out all categories of the data presented to the net during the training phase. However, by common neural nets, there is a problem. At least for every different status of the system/patient, one single neuron has to be implemented or, if we don't know how many states exist, more neurons than existing states have to be implemented in the network.

To work around this challenge, we developed a new kind of processing and interpretation strategy "Computing with Activities" (CWA-Method) [20, 21]. Out of this theory, we interpret the overall activity of the whole net rather than the activity of a single neuron. This interpretation is near to the neurological assumption that the neuron ensemble activity pattern is an accurate model of what happens in the real world, better than classical simulated neural net theory. An example will show us how powerful this new theory is.

Using the classical information theory of the simulated neural nets, we can store in a net, containing 200 neurons, 200 different possible states of a single neuron. If we use the CWA-Method and define that our simulated neurons can occupy five different states, (such as five different firing modes of a fixed time interval of a natural neuron) we can code 5^{200} simulations in the same net. For us, the coding seems to be nearer to nature. This is similar to how a honeybee can communicate information to its colleagues when looking for “flowers”.

Using the CWA-Method also means that slight changes in the data sets will also lead to slight changes in the categorizer result. Within the CWA-Method, the missing link to build a management systems with great differences in patient status will lead to great differences in the activity pattern of our basic categorization module and vice versa.

Figures 1a and 1b show some examples of such an activity based categorizer. The upper examples show a small difference in the data sets, the lower a larger difference. It is important to mention, that the data sets used here have 20

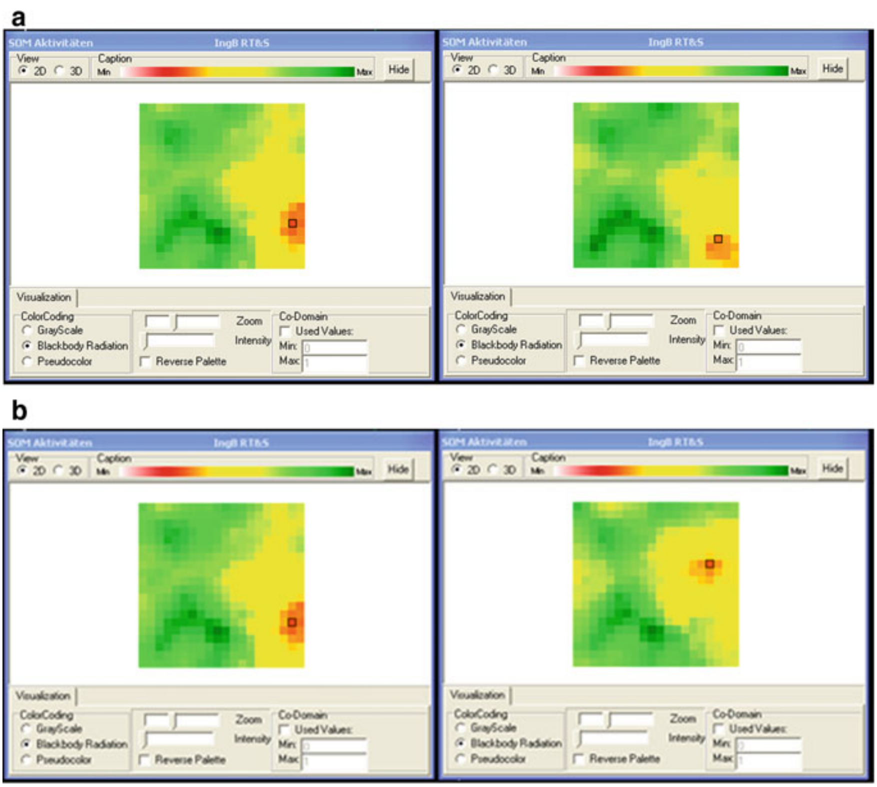

Fig. 1 **a** CWA-Method explained by similar patient’s categorization. **b** CWA-Method explained by unequal patient’s categorization

dimensions, this means that 20 parameters (here 20 different answers to 20 different questions) have been combined to categorize different patients regarding their similarity in behaviour and status.

2.4 Categorizations Criteria, Color Coding and Trend Analysis

Once a patient has answered all questions, the neural net structure categorizes the patient as described above. The system requires an adequate machine-user-interface which enables the medical staff to interpret the neural based categorization in an intuitive and quick way. For this reason, we incorporated a special interpretation module, which analyzes the neural activity pattern in a way that four different general categorization classes describe the momentary state of a patient. These classes are combined with a kind of "next to do list," which presents a reference of therapeutic interventions. These categories and therapeutic interventions are:

- Green: patient's state is OK, no action is needed
- Yellow: patient's state is more or less OK, but has to be supervised and improved
- Orange: patient's sate is not OK, action is needed
- Red: patient's state is alarming, prompt action is needed.

3 Functionality and Structure of a CI-Based Personal Diabetes Management Tool

The realization of a CI-based personal diabetes management tool was taken into account several years ago, whereby we decided to use a C++ based system, connected to a common PostgreSQL Database.

Because of the sensibility of the personal data, all data is encrypted. The system itself is protected by a 9-number PIN code, as shown in Fig. 2.

After logging in as a patient or as a doctor, the patient's personal data is collected by a standard user interface, which is shown by Fig. 3. This electronic form is divided in three main parts:

> Left hand side at the top the "name and address part" and some of the data, like name of birth, first name and date of birth are protected and therefore cannot be changed, even by the medical staff. An extra window represents the employer's part (shown on right hand side). The stored data can be changed and are automatically available for printing a certificate of disability. The actual status part—shown in the left middle part of Fig. 3—represents the actual body of data, like weight, height, gender and the patient actual state; these are data that the system analyzes.

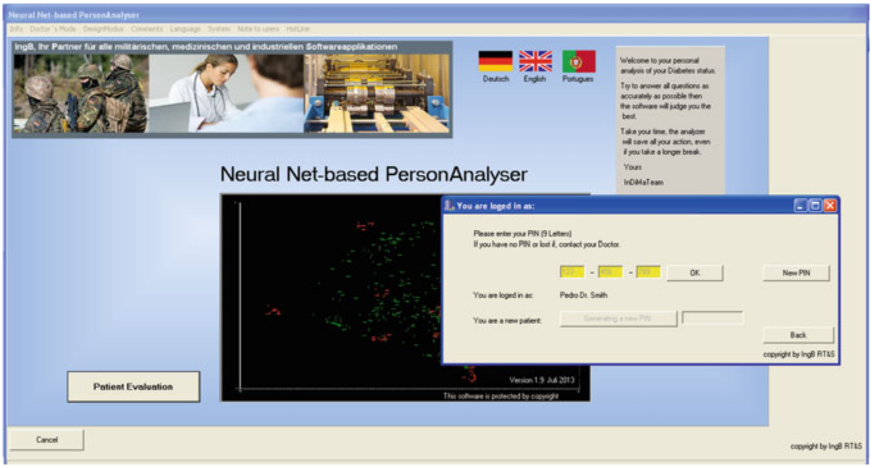

Fig. 2 Start form of the CI-based personal diabetes management tool

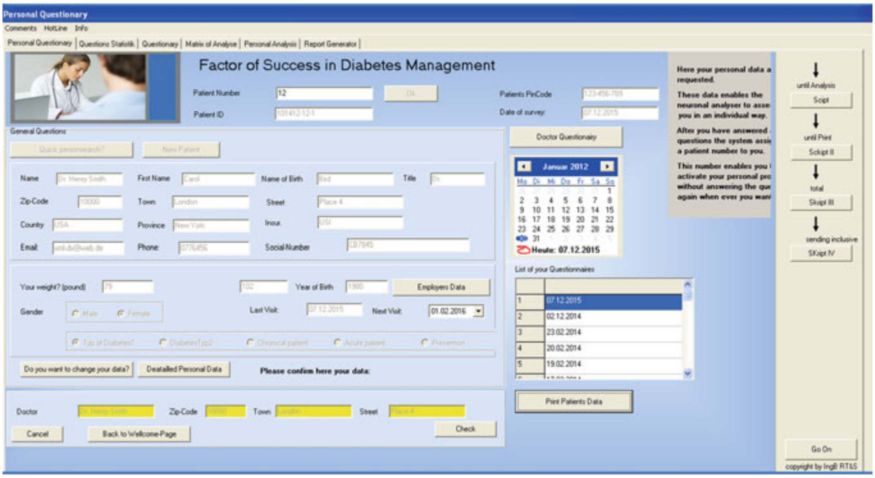

Fig. 3 Patient’s data input mask

At the button of the form the doctor’s data are shown. The system itself is protected also via this doctor’s data; means, changing this data requires a change of the safety keys. At the right hand side of the form some services functions, like a calendar, the history of all sessions of the patient and the printer routines to print the personal file and/or the old reports are documented.

In addition, in this personal data sheet, two other sheets are involved. The first of them involves the data of the employer and the insurance, as shown in Fig. 4.

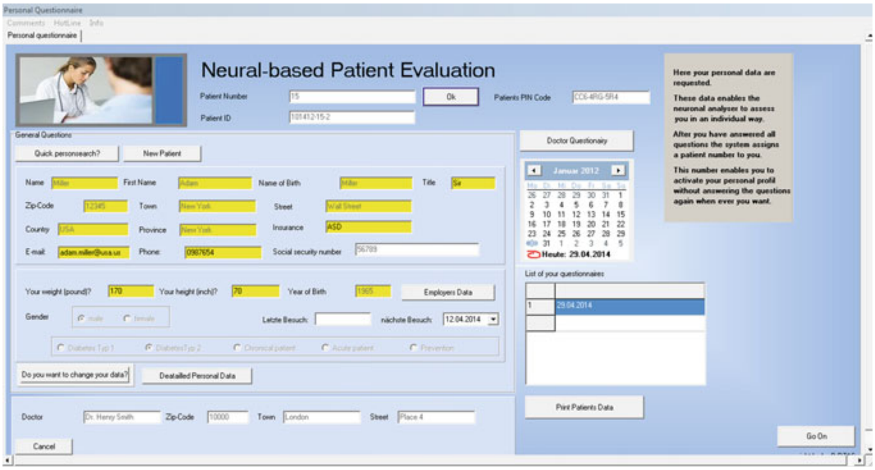

Fig. 4 Patient's data input mask including employer's data

Also, if the "Doctor's Modus" is selected, secondary information of the patient's history, additional diseases and former therapeutic interventions can be recalled. The principal structure of the additional data sheet is visualized in Fig. 5.

Sometimes it is useful to have a short patient's details printed out. For that reason, in the system patient's overview, such a file format is integrated. This can be printed out and/or be included in an existing data collection file or integrated in a database system used in the doctor´s office. Figure 6 shows the general structure of the patient's file.

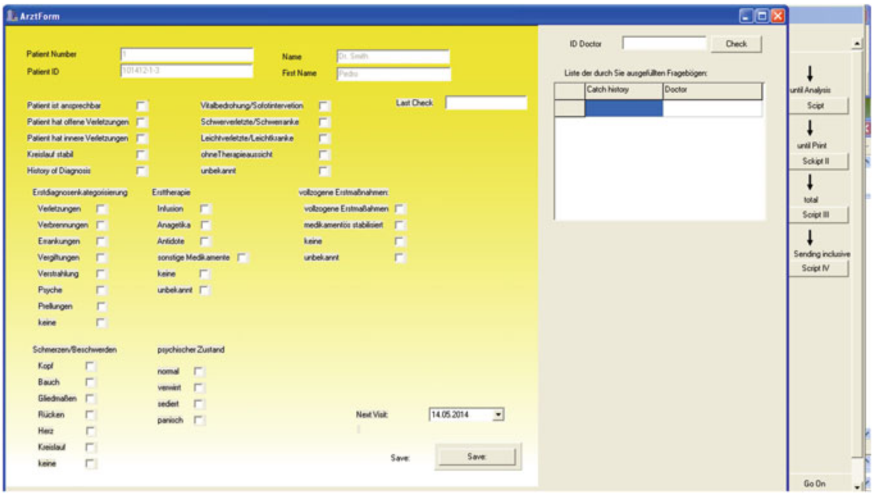

Fig. 5 Secondary patient's data sheet

Ihr Pin:	123-456-789

Name		
	Familienname	Brinkmann
	Vorname	Nora
	Geburtsname	Brinkmann
	Anrede/Titel	Frau
Adresse/Kontakt		
	Land	Deutschland
	Provinz	Niedersachsen
	Postleitzahl	38678
	Stadt	Clausthal
	Strasse	Einersberger Blick 16
	Hausnummer	
	Telefon	05323727104
	Handy	
	Fax	
	Email	xmkdx@web.de
Versicherungsangaben		
	Krankenkasse	dkv
	Versicherungsnummer	21-1234-567-064

Fig. 6 Form and style of the patient's file

After the personal data sheet has been completed, the patient is guided through the different questionnaires under the following categories:

– disease status and disease history
– physical status
– psychological status
– social status
– familiar status
– status of cooperation
– self-assessment, and
– foreign assessment.

Any of these items can be selected from the first sheet of the questionnaire, as shown in Fig. 7.

If an item, also called "key-factor", is completed, the system announces that every question was answered, as shown on the right hand side of Fig. 7. After selecting an item, the system offers the different questions and the possibility to answer via a ranking, as shown in Fig. 8a.

After the questionnaire is completed, the system will ask which items should be analyzed. This is done by a decision mask, as shown in Fig. 8b.

Once the patient and doctor's work inputs are completed, the system generates the diabetes status, the trend and the prognosis of the patient's status with help of the neural nets. All these items are visualized via a simple visual output as shown by Fig. 9.

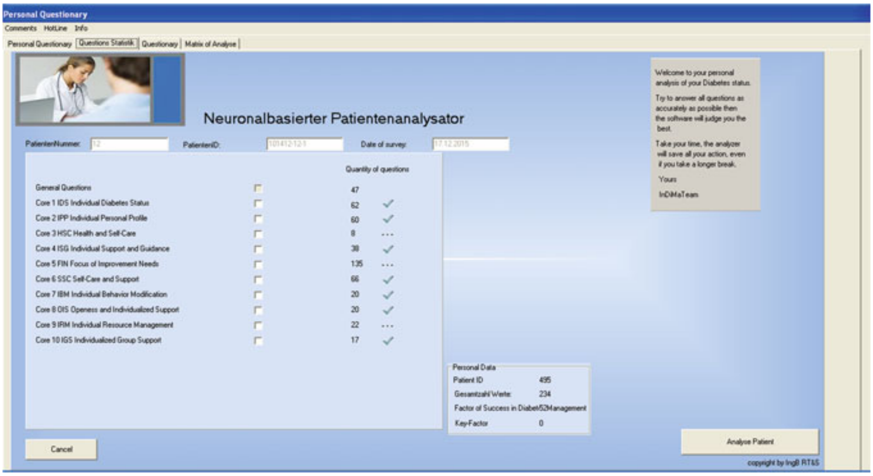

Fig. 7 First sheet of the questionnaire

The color-coded patient state analysis shown in Fig. 9 contain the following:

1. The overall state of the patient, represented by the left hand side block
2. The block in the middle shows the development of the patient in the different categories which are analysed
3. The block right hand side represents the analysis and trend of each question.

These three different categorizations were used to evaluate the system during the R&D-phase of development for best fit of a patient's status. The left columns of each block point out the average of the analysis of all data (here the overall analysis and the trend analysis of the patient's data), whereas, the middle column represents the neural net categorization of the states following the four classes, green, yellow, orange and red. The right column represents the categorization of the neural nets by corresponding rainbow colors. By rainbow colors the status of the patient can be shown much more gradual, because instead of four colors, 256 colors are used. But for a quick overview, it is helpful if a categorization of four colors is presented. This can be pointed out very clearly by the categorization of the single questions (right hand side block). On left hand side, the traditional four color-coding is shown, while the right column shows the categorization by the corresponding rainbow colors. As our investigations showed, the chosen color-coding enables a detailed analysis of patients within "one view", especially the break down from the global categorization of the overall state of the patient leading to an effective estimation of diabetes management.

Figure 9 shows the momentary status of a patient. To ensure that therapeutic measures are successful over the time, or to identify deteriorations on one or several areas, a statistical module which analyses the categorization results over time can be implemented. Based on the database entries of the patients, this module identifies

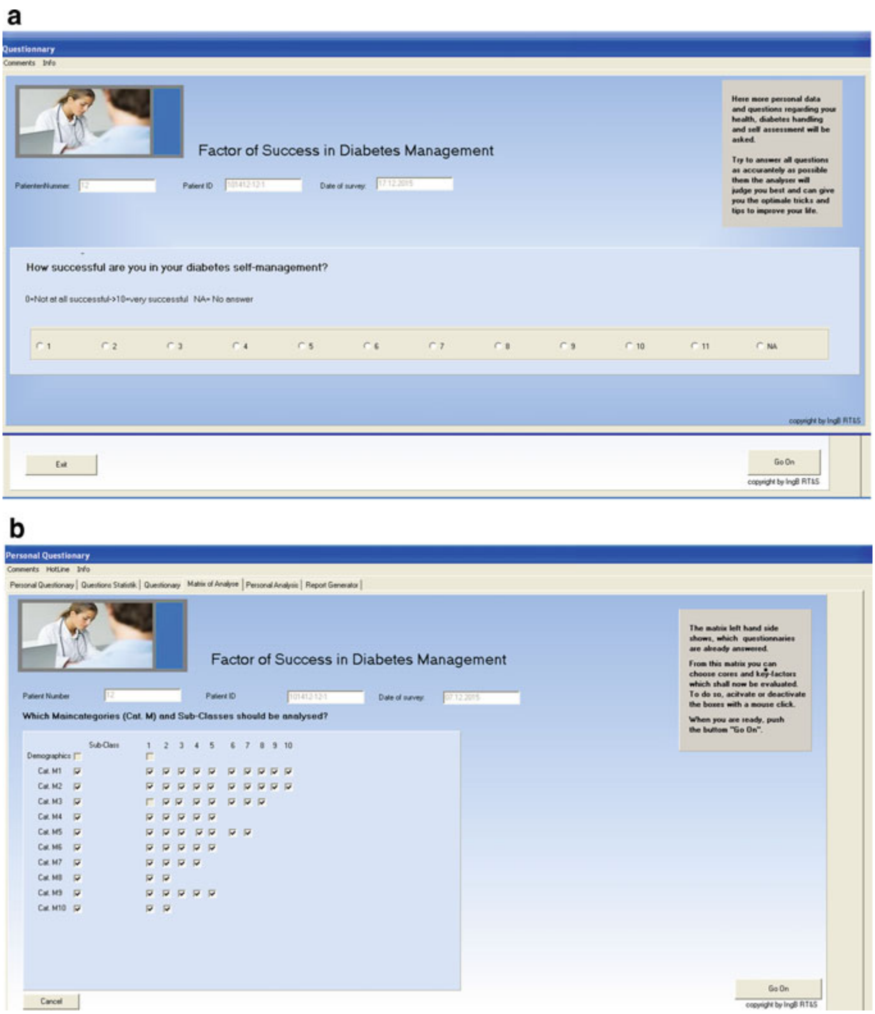

Fig. 8 **a** Question sheet of the questionnaire. **b** Decision mask of the questionnaire

three different trends, again on basis of our color coding and visualises them in special charts, as shown in Fig. 3. Out of these charts, another module calculates a trend of prognosis, in which statistical blips are taken into account. Furthermore, different time intervals for the trend of prognosis can be chosen, which gives the medical staff the opportunity to analyse momentary and slow changes. Moreover, the medical stuff or the patient themselves can choose alternate categorization of global status or the categorization by single questions. In that way, the tools identify the weak or the strong points in patient's behaviour and/or patient's handling of the disease. At least in that way, the doctors, the medical stuff, the social environment and the patient are empowered to supervise and interpret the momentary and past states of the patient's diabetes.

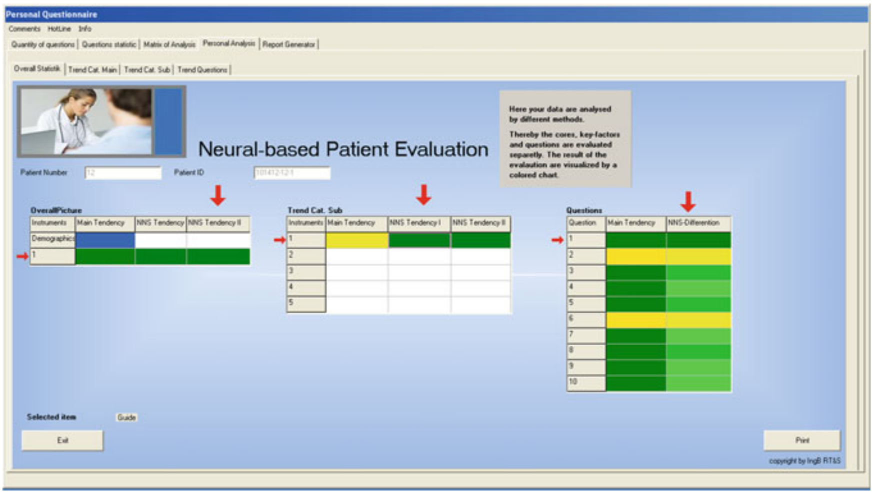

Fig. 9 Color-coded patient state analysis

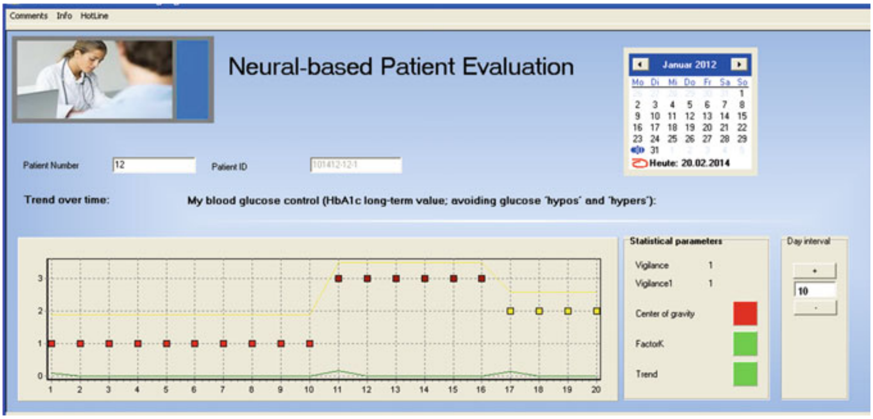

Fig. 10 Trend analysis and trend visualization of a patient over 20 examinations

Image 3 shows, in detail, the chart of the color-coded categorizations of the blood glucose control (HbA1c) of a patient over 20 examinations (left hand side). The values for the HbA1c (high or low) during the course of management can be easily pointed out by the Chart. The middle block shows the statistical parameters, the centre of gravity (the overall middle value over all examinations), and the Factor K, a special statistical process control which points out a prognosis for the next two weeks and the momentary trend over the next 10 days. Figure 10 shows a typical patient at the beginning of therapy. The HbA1c was high to low (red), but during the first therapeutic intervention, it shows improvement and thus the

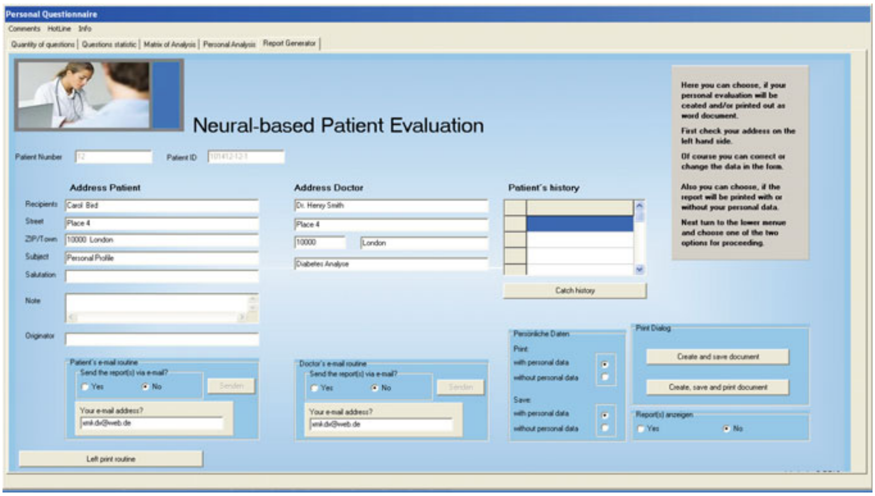

Fig. 11 User interface of the report generator

prognosis square shows a green color. As the duration of the improvement of the HbA1c value holds for a long time without significant fluctuation, the Factor K value square is green colored.

Our tool has the ability to archive the categorization and trend analysis in a PDF-document. This document can be stored in an anonymous or personalized form and can be printed out directly and/or sent via email to the patient or a medical centre. Furthermore, our report generator allows one to select further examination results for printing and/or controlling. Figure 11 shows the user interface of this reporting and printing dialogue with all optional possibilities of the documentation and sending routines.

A standard form of a report is shown in Fig. 12. At the top of the report, the personal data is (optional) given, followed by the legend of the color-coding. Next, the different questions' text and their classical and neural based categorization results are listed. The report of the questions ends with the chart of the completed questionnaires and the long and short time prognosis, coded again by the colors of the categorization and a short text segment.

4 Some Statistics of the Neural Net Condition Phase

We condition and test the system with two different data sets to explore the data sets of the partner company SMO Networks. The first data set, collected in the USA, contained 1024 patients' questionnaire data; 501 of Diabetes Type I and 523 of Diabetes Type II. The second data set, collected in Germany, contains 612 patients' questionnaire data of Diabetes Type I and 564 of Diabetes Type II. Different social,

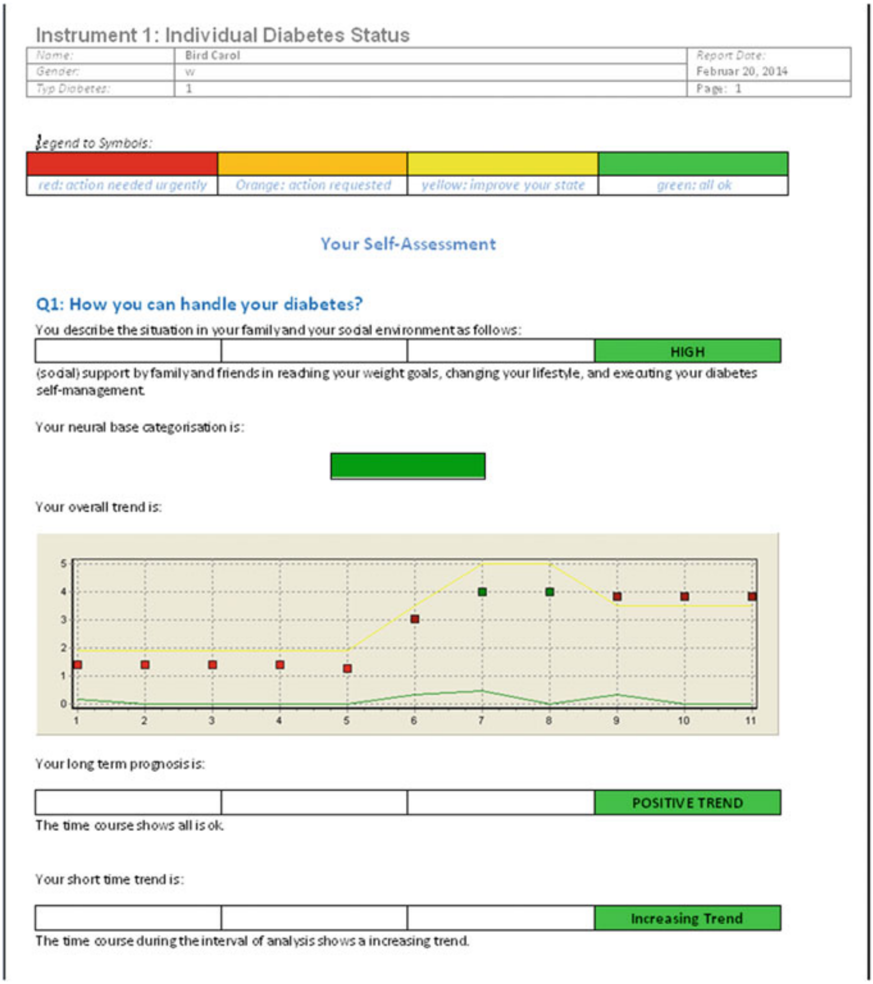

Fig. 12 Report of an exemplary patient categorization

ethnic and educational groups have been recorded to empower the neural nets to differentiate adequately between the wide ranges of data. After the training phase of the neural nets, the statistical distribution of the categorized data sets were evaluated and compared with the literature to ensure our system reflects reality. A typical statistical distribution of "bad data set categorization by a neural net" is shown by Fig. 13.

As can be clearly pointed out by Fig. 13, the neural net represents three of the four colors only (Column 1 represents the red color, column 2 the orange, column 3 the yellow and column 4 the green). However, it is important to remember that the reason for this may well lie in the unbalanced structure of the data itself, as well as in the conditioning of the neural network.

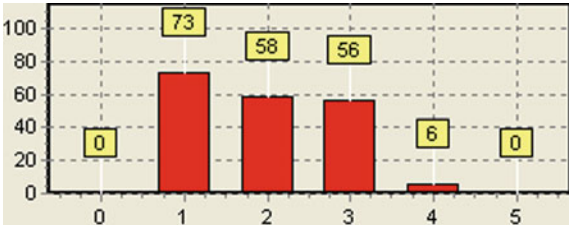

Fig. 13 Unbalanced statistical distribution of patient's data, not used for conditioning the neural net library

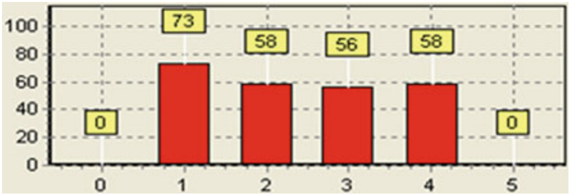

Fig. 14 Balanced statistical distribution of patients data, used for conditioning the neural net library

Figure 14 shows a well-conditioned net, based on a well-balanced data set. In this data set all four classes (all four color based categorization classes) are represented by nearly the same number of patients.

Using only such data sets, we conditioned a library of neural nets, representing all kinds of combinations of the questionnaires, where in each net all kinds of "possible patient's states" are stored.

Remark: To ensure the right categorization of extremely abnormal patients' data sets some simulated patient data sets with extreme states have to been taken to ensures that all kinds of patients can be categorized by the system in a logical and comprehensible way.

At least we evaluate the final system regarding its economy of time. For this we asked test persons to supervise and assess patients by common methods like paper or computer based patient medical files, Excel data sheets or conversation by comparison of using our system. After a short training phase, our test persons needed a factor ten times less for a patient evaluation; which means the system enables additional a fundamental cost saving.

References

1. American Diabetes Association, Diagnosis and Classification of Diabetes Mellitus. Diabetes Care **27**(1) (2004)
2. American Diabetes Association, Standards of medical care in diabetes—2014. Diabetes Care **37**(1), S14–S80 (2014)
3. Ellrodt, G., Cook, D.J., Lee, J., Cho, M., Hunt, D., Weingarten, S.: Evidence-based disease management. JAMA **278**, 1687–1692 (1997)

4. Szecsenyi, J., Rosemann, T., et al.: German diabetes disease management programs are appropriate for restructuring care according to the chronic care model: an evaluation with the patient assessment of chronic illness care instrument. Diabetes Care **31**(6), 1150–1154 (2008)
5. Reuter, M., Bohlmann, S.: Supervising multicut aggregates by special neural nets. In: World Automation Congress (WAC), 24–28 Juni 2012, Puerto Vallarta, Mexico (2012)
6. Reuter, M., Bohlmann, S.: Einsatz von neuronalen Netzen zur automatischen Überwachung einer Fertigungsanlage im Online-Modus. VDE-Kongress 2014 "Smart Cities". Frankfurt (2014)
7. Reuter, M., Bohlmann, S.: Personal diabetes management tools based on hybrid neural nets. In: BMT 2014—48th DGBMT annual conference, 8–10 October 2014, Hanover, Germany (2014)
8. Bailey, R.A., Pfeifer, M., Shillington, A.C., et al.: Effect of a patient decision aid (PDA) for type 2 diabetes on knowledge, decisional self-efficacy, and decisional conflict. BMC Health Serv. Res. (2015)
9. Garber, A., Abrahamson, M., Barzilay, J., Blonde, L., Bloomgarden, Z., Bush, M., et al.: AACE/ACE Comprehensive diabetes management algorithm 2015. Endo Pract. **21**, 438–447 (2015)
10. Nam, S., Chesla, C., Stotts, N.A., Kroon, L., Janson, S.L.: Barriers to diabetes management: patient and provider factors. Diabetes Res. Clin. Pract. **93**, 1–9 (2011)
11. King, D.K., Glasgow, R.E., Toobert, D.J., Strycker, L.A., Estabrooks, P.A., Osuna, D., et al.: Self-efficacy problem solving, and social-environmental support are associated with diabetes self-management behaviors. Diabetes Care **33**(4), 751–753 (2010)
12. Paget, L., Salzberg, C., Scholle, S.H.: Building a strategy to leverage health information technology to support patient and family engagement. http://www.ncqa.org/HEDISQualityMeasurement/Research/BuildingaStrategytoLeverageHealthInformationTechnology.aspx. Accessed 10 Oct 2015
13. Streja, D.A., Rabkin, S.W.: Factors associated with implementation of preventive care measures in patients with diabetes mellitus. Arch. Intern. Med. **159**, 294–302 (1999)
14. Paddock, E.P., Veloski, J., et al.: Development and initial validation of a patient satisfaction with pharmacy performance questionnaire (PSPP-Q) evaluation & the health professions **33** (2), 197–215 (2010)
15. Grogan, S., Conner, M., et al.: Validation of a questionnaire measuring patient satisfaction with general practitioner services. BMJ Qual. Saf. 9(4), 210–215 (2000)
16. Grogan, S., Conner, M., Willits, D., Norman, P.: Development of a questionnaire to measure patients' satisfaction with general practitioners' services. Br. J. Gen. Pract. **45**(399), 525–529 (1995)
17. Kohonen, T.: Self-organized formation of topologically correct feature maps. Biol. Cybern., 59–69 (1982)
18. McCulloch, W.S., Pitts, W.: A logical calculus of the ideas immanent in nervous activity. Bull. Math. Biophys. **5**, 115–133 (1943)
19. Rosenblatt, F.: The perceptron: a probabilistic model for information storage an organization in the brain. Psychol. Rev. **65**, 386–408 (1958)
20. Reuter, M., Bostelmann, S.: Computing with activities, WHU-structures and a quantization model of the neural nets, WSOM 2005, Paris, France (2005)
21. Reuter, M., Tadjine, H.: Computing with activities III: chunking and aspect integration of complex situations by a new kind of Kohonen Map with Whu-Structures (Whu-SOMs). IFSA. Beijing, VRC (2005)