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I-AFYA: Intelligent System for the Management of Diabetes in Kenya

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ABSTRACT

Computational Intelligence approaches have gained increasing popularity given their ability to cope with large amounts of clinical data and uncertain information. The treatment offered for diabetes aims to keep a patients' blood glucose level as normal as possible and to prevent health complications developing later in their life. Researchers and developers have created diabetes applications and systems that already are frequent on various application stores and shelves. Applications running on artificial intelligence (AI) and cognitive computing models offer promise in diabetes care. This is given the fact that diabetes is a global pandemic. An estimated 425 million people worldwide have diabetes, accounting for 12% of the world's health expenditures and yet one in two persons remain undiagnosed and untreated. Type 2 diabetes is driven by the global obesity epidemic and a sedentary lifestyle that overwhelms the body's internal glucose control requiring exogenous insulin. In Kenya alone, diabetes is a leading cause of kidney failure, lower limb amputations and adult-onset blindness. Thus, research on diabetes care using technological (ICT) solutions will continue to dominate the discussion for quite some time. The early detection of diabetes is of paramount importance. Generally, a physician diagnoses diabetes by evaluating the current test results of a patient or by comparing the patient with other patients who have the same condition. The early detection and screening for individuals with impaired glucose tolerance can help lower risk of developing diabetes and reduce the long-term burden to individuals and health services. For this reason, artificial intelligent systems for diagnosing diabetes have been an item for research for some time. The use of intelligent systems in the Kenyan health care system can help lower the cost of diabetes treatment besides increasing the access and quality of health care provided to diabetic patients.

Keywords: Diabetes mellitus, Artificial Intelligence, Decision tree, Conceptual Design, KNN, Agile, I-Afya, Regression Analysis, Diabetes Kenya, Support Vector Machine, Reinforcement Learning, and Knowledge Discovery in Databases.

1 Introduction

The World Health Organization estimates that 80 percent of the responsibility for chronic disease management rests with patients. The patients need to follow daily care routines, make life style changes and improve communication with caregivers (Sobel, 2003; NHS Modernization Agency, 2004). Computational Intelligent systems offer a unique opportunity to empower individual patients in improving their compliance with care management and improving health outcomes and reducing the cost of

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treatment. By use of an Intelligent and interactive decision-making system, the application of diabetic health care can be improved at key touch points.

Application of artificial intelligence (AI) and cognitive computing models have increased efficiency in the detection and treatment of diabetes. This is a useful issue for development and research given that diabetes is a global pandemic. Type 2 diabetes is driven by the global obesity epidemic and a sedentary lifestyle that overwhelms the body's internal glucose control requiring exogenous insulin. Optimal care for persons with diabetes often is hampered by the absence of real-time, key health data necessary to make informed choices associated with intensive therapy and tight diabetes control.

Artificial Intelligence offers the promise of making both real-time structured and unstructured health data available for the care of diabetic patients. The Turing Archive for the History of Computing defines AI as “the science of making computers do things that require intelligence when done by humans.” AI covers a broad range of approaches to simulating human intelligence and performing various reasoning tasks, such as visual perception, speech recognition, analytics, decision-making, and translation between languages. The purpose of this study is to build a computational model for the effective treatment of diabetes in the Kenyan health care system. Such a system would take into consideration underlying factors that influence diabetic prescriptions such as individual history, key patient parameters such as glucose level, body mass index (BMI), insulin, blood pressure, age and diabetic pedigree.

2 Issues

Diabetes Mellitus refers collectively to a group of diseases resulting from dysfunction of the glucoregulatory system. The International Diabetes Federation estimates that, by 2017, diabetes affected 425 million people worldwide, of whom, 4 million died in the same year. These figures are expected to increase dramatically in the coming decades, placing a rising burden on health care systems. This is especially so in the developing countries such Kenya. A wide range of therapeutic options is available for patients with diabetes.

Intelligent algorithms are widely used in data driven methods to support advanced analysis and provide individualized medical aid. In the Kenya, the treatment of diabetes is both costly and sometimes even unaffordable. Many complications have occurred in cases where diabetes was not detected on time and treated. The complex identifying process usually results in the patient visiting a diagnostic centre and consulting a doctor. The complexity of diabetes prognosis and management provides a problem window for computational models to provide key solutions that empower both patients and caregivers in their everyday life. This will provide a computational prototype model that prognosticates the likelihood of diabetes in a patient with maximum accuracy.

3 General Objectives

The general objective of the research was to build an Intelligent Computational Model that could improve diabetic management for patients in the Kenyan healthcare system as well as help solve the attendant challenges of cost, access and accurate diagnosis. The first objective was to develop machine learning computational model for the detection and diagnosis of diabetes. This would improve on the accuracy in the prognosis of diabetes. Secondly the research sought to develop an intelligent system capable of processing of symptoms data and information that could help improve the treatment outcomes of a diabetic patient. Thirdly the system developed would have a data visualization capability for effective communication as well a data model for diabetes- diabetes types, risk factors, symptoms and the subsequent diagnosis or prediction.

4 Related Work

4.1 Introduction

Diabetes mellitus (DM) is defined as a group of metabolic disorders exerting significant pressure on human health worldwide. Extensive research in all aspects of diabetes (diagnosis, etiopathophysiology, therapy, etc.) has led to the generation of huge amounts of clinical data. Design of computational models for diabetes diagnosis has been an active research area for the past decade.The potential of AI to enable diabetes solutions has been investigated in the context of multiple critical management issues. In this research, we use the diabetes management categories that include blood glucose control, prediction, detection of adverse glycaemic events, insulin calculation, life-style tendencies and the daily-life support in diabetes management. AI is attracting increased attention in this field because the amount of data acquired electronically from patients suffering from diabetes has grown exponentially. By means of complex and refined methods, AI has been shown to provide useful management tools to deal with these incremental repositories of data.

Artificial intelligence is defined as a branch of computer science that aims to create systems or methods that analyse information and allow the handling of complexity in a wide range of applications (in this case, diabetes management). Although the application of AI algorithms involves highly technical and specialized knowledge, this has not prevented AI from becoming an essential part of the technology industry and contributing to major advances within the field. This section will provide a short review of several well-known computational intelligence paradigms. In this study, we categorized methodologies with respect to the objective sought: to explore and discover information, to learn using information, or to extract conclusions from information. The figure 1 below depicts a taxonomy of artificial intelligence methods.

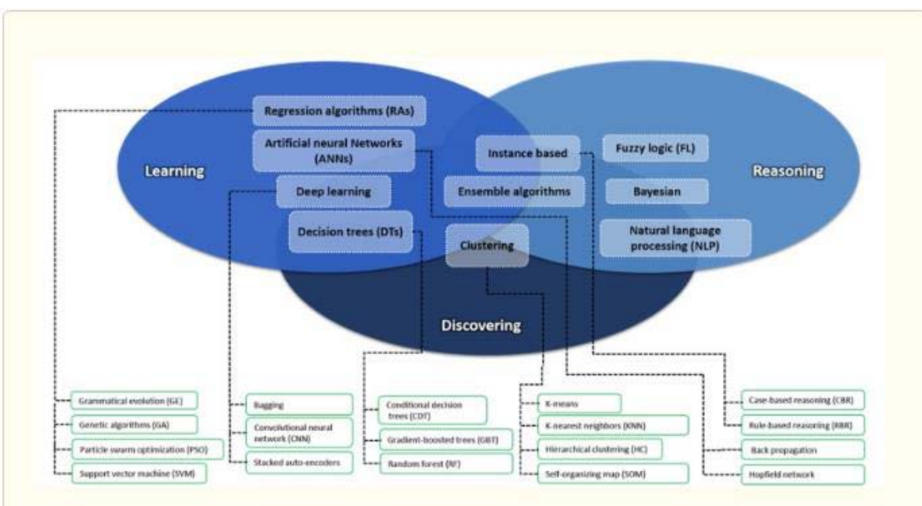

Figure 1: Artificial Intelligence Methods

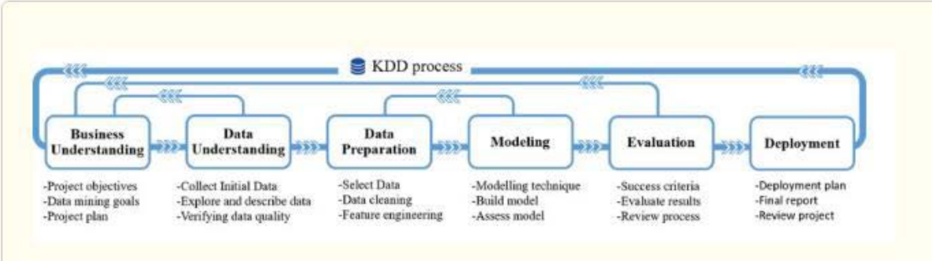

Figure 2: Knowledge Discovery Process

4.2 Clinical and Computational Intelligence

Chronic conditions like cancer, diabetes, mental disorders, cardiovascular and respiratory diseases account for 36 out of the 57 million deaths annually, thus the need for Business Intelligent systems to help in the management. According to Ngemu, 2015, Computational Intelligence is a broad category of applications and technologies for gathering, storing, analyzing and providing access to data to help enterprise users make better data models. Computational and business intelligence improves decisions by supplying timely, accurate, valuable, and actionable insights. With the rapid advancement and development of Information and Communication Technologies (ICT), health care providers are now able to generate, collect and distribute huge amounts of data from internal and external sources, and use this data in creating efficient models for the detection, diagnosis and treatment of diabetes.

Several studies applied artificial intelligence to systems aimed at supporting patient decisions by issuing advice regarding meals, exercise, or medication. Research groups at the Imperial College London performed an extensive study of an insulin bolus calculator based on case-based reasoning methodology. Their approach, which manages various dynamically optimized diabetes scenarios, was proven in a clinical trial to be a safe decision support tool. Additionally, this approach was demonstrated to improve glycaemic control in diabetes management. A similar approach was presented recently by another group, which also proposed an insulin bolus calculator based on case-based reasoning but, in contrast to other bolus calculators, it used a novel temporal retrieval algorithm. More recently, another study presented an approach based on artificial neural networks (ANN) and K-Nearest Neighbours to optimize bolus calculation by patients. The results revealed that it was better at reducing the blood glucose risk index value than other approaches. Finally, Lee et al proposed an advisory treatment system that provides insulin, meal, and exercise recommendations using a decision tree algorithm. The study, which compared rule-based reasoning and k-nearest neighbour algorithms, concluded that the decision tree based algorithms are best suited to this approach.

4.3 Conceptual Design

Diabetes is a disease that occurs when the insulin production in the body is inadequate or the body is unable to use the produced insulin in a proper manner, as a result, this leads to high blood glucose. The body cells break down the food into glucose and this glucose needs to be transported to all the cells of the body. The insulin is the hormone that directs the glucose that is produced by breaking down the food into the body cells. Any change in the production of insulin leads to an increase in the blood sugar levels and this can lead to damage to the tissues. Diabetes is a disease that occurs when the insulin production in the body is inadequate or the body is unable to use the produced insulin in a proper manner, as a result, this leads to high blood glucose.There are three main types of diabetes:

Type 1 – Though there are only about 10% of diabetes patients have this form of diabetes. The disease manifest as an autoimmune disease occurring at a very young age of below 20 years hence also called juvenile-onset diabetes. In this type of diabetes, the pancreatic cells that produce insulin have been destroyed by the defence system of the body. Injections of insulin along with frequent blood tests and dietary restrictions have to be followed by patients suffering from Type 1 diabetes.

Type 2 – This type accounts for almost 90% of the diabetes cases and commonly called the adult-onset diabetes or the non-insulin dependent diabetes. In this case, the various organs of the body become insulin resistant, and this increases the demand for insulin. At this point, pancreas does not make the required amount of insulin. To keep this type of diabetes at bay, the patients have to follow a strict diet, exercise routine and keep track of the blood glucose.

Gestational diabetes – is a type of diabetes that tends to occur in pregnant women due to the high sugar levels as the pancreas do not produce sufficient amount of insulin. Taking no treatment can lead to complications during childbirth. Controlling the diet and taking insulin can control this form of diabetes.

Though both Type 1 and Type 2 diabetes cannot be cured, they can be controlled and treated by special diets, regular exercise and insulin injections. The complications of the disease include neuropathy, foot amputations, glaucoma, cataracts, increased risk of kidney diseases and heart attack, stroke, and many more.

The data is collected from real time repository and it conforms to Type II diabetes based on the given attributes. The research explored the use of Decision Tree and K-Nearest Neighbor Classifier as machine learning techniques in diagnosing diabetes. The main objective being to forecast if the patient has been has diabetes using data mining tools from the medical data available.

Several prototypes of diabetes care systems have been designed and implemented. The first general steps is to ensure that that system will capture new patient data accurately. In most cases, it is upon the patient to provide these data and there should be a support mechanism to provide the data. The proposed i-Afya System for diabetes care is composed of an interactive and graphical user interface for capturing data and a core back end functionality that does the data interpretation and processing. After the processing, visual presentations of the data will be presented. The core processing includes a classification algorithm using decision tree model. The system has transformation capabilities for the learning, which includes replacing missing values and normalization of values. Figure 4 below gives a high-level view of the system model.

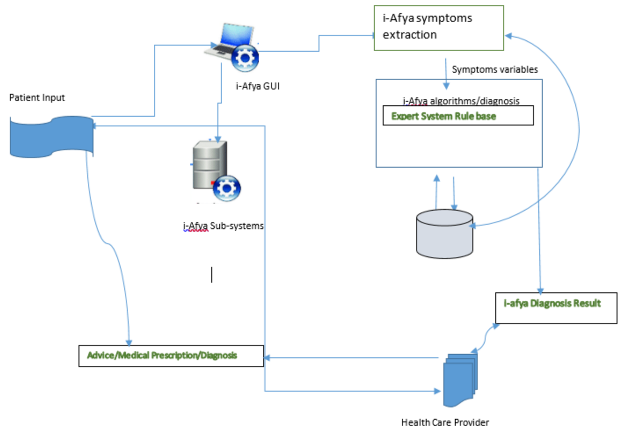

Figure 4: System High Level Architecture

5 Research Approach

Two algorithms namely decision tree classification and regression tree (CART) algorithm and KNN have been used to create the model for diagnosis. The data was divided into a training set and formatted using CVS. It was validated using the cross-validation technique and percentage split technique.

5.1 Data Sources

A cross sectional study conducted for people living with diabetes in Kenya by Novartis research team in Nairobi and other towns by June 2015 pre-released data indicated that diabetes care receivers under Novartis were about two thousand. Data for carrying out this research and project was sourced from the Diabetes Association of Kenya, which presented the status of various health care providers as well as the quality of health care provided to diabetic patients. Selected interviews were also done with Physicians specializing in diabetes treatment. Nairobi provided the bigger samples of the data as it had 70% of the registered patients. The estimated sample size of the data was arrived by the satisfaction of the criteria.

The data was tested using the cross-validation technique and the percentage split technique. The dataset pre-processing was done using R programming language. Algorithm, which has libraries for normalizing data. Additional data operations were performed on the dataset to replace missing values. The Processed dataset was then parsed through feature selection wherein sets of attributes are typically deleted from the dataset. The final processed dataset was parsed through R scripts for prediction of any new instances using the developed i-Afya system. Both the KNN and decision tree algorithms were used.

5.2 Data Description and Pre-Processing

The clinical data harvested from Diabetes Kenya and the data sources was unstructured and had irrelevant attributes and thus required be prepared using relevant formats, processing and transforming for data evaluation and validation. The data was collected from real time repository and conformed to both Type 1 and Type II diabetes based on the given attributes. The data was collected and keyed into the model for learning purposes.

The data set had ten attributes, which when modelled using R language. The data had eight attributes for processing namely, BMI, skin thickness, insulin, age, number of pregnancies(for female patients), glucose, blood pressure and a variable known as diabetespedigreefunction. Exploratory data analysis and feature selection were carried out using R libraries and a statistical summary developed as shown in figure 6. After modelling of the data, the algorithms for implementing the system prediction module were developed and employed. The raw data was run on CSV data. The correlation between numeric variable was also implemented as well as the correlation between the variables and the outcome as shown in figure 9 and figure 10.

```
Statistical summary

```{r}
summary(diabetes)
```

  Pregnancies   Glucose   BloodPressure   SkinThickness
 Min.   : 0.000   Min.   : 0.0   Min.   : 0.00   Min.   : 0.00
 1st Qu.: 1.000   1st Qu.: 99.0   1st Qu.: 62.00   1st Qu.: 0.00
 Median : 3.000   Median :117.0   Median : 72.00   Median :23.00
 Mean   : 3.845   Mean   :120.9   Mean   : 69.11   Mean   :20.54
 3rd Qu.: 6.000   3rd Qu.:140.2   3rd Qu.: 80.00   3rd Qu.:32.00
 Max.   :17.000   Max.   :199.0   Max.   :122.00   Max.   :99.00
    Insulin   BMI   DiabetesPedigreeFunction   Age
 Min.   : 0.0   Min.   : 0.00   Min.   :0.0780   Min.   :21.00
 1st Qu.: 0.0   1st Qu.:27.30   1st Qu.:0.2437   1st Qu.:24.00
 Median : 30.5   Median :32.00   Median :0.3725   Median :29.00
 Mean   : 79.8   Mean   :31.99   Mean   :0.4719   Mean   :33.24
 3rd Qu.:127.2   3rd Qu.:36.60   3rd Qu.:0.6262   3rd Qu.:41.00
 Max.   :846.0   Max.   :67.10   Max.   :2.4200   Max.   :81.00
    Outcome
 Min.   :0.000
 1st Qu.:0.000
 Median :0.000
 Mean   :0.349
 3rd Qu.:1.000
 Max.   :1.000
```

Figure 5

Figure 6 and 7 shows a brief description of the dataset that were being modelled and the relevant attributes.

R Console | data.frame 6 x 9

	Pregnancies <int>	Glucose <int>	BloodPressure <int>	SkinThickness <int>	Insulin <int>	BMI <dbl>
1	6	148	72	35	0	33.6
2	1	85	66	29	0	26.6
3	8	183	64	0	0	23.3
4	1	89	66	23	94	28.1
5	0	137	40	35	168	43.1
6	5	116	74	0	0	25.6

6 rows | 1-7 of 9 columns

Figure 6 R Dataset Model

R Console | data.frame 6 x 9

SkinThickness <int>	Insulin <int>	BMI <dbl>	DiabetesPedigreeFunction <dbl>	Age <int>	Outcome <int>
35	0	33.6	0.627	50	1
29	0	26.6	0.351	31	0
0	0	23.3	0.672	32	1
23	94	28.1	0.167	21	0
35	168	43.1	2.288	33	1
0	0	25.6	0.201	30	0

Figure 7 R Dataset Model

Figure 8 shows the distribution which shows that all variables have reasonable broad distribution.

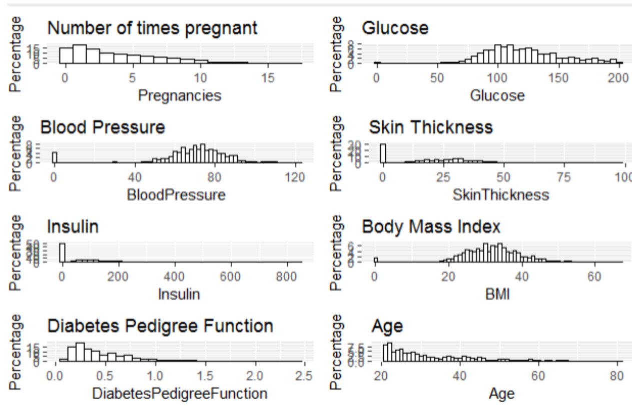

Figure 8 R Dataset Distribution

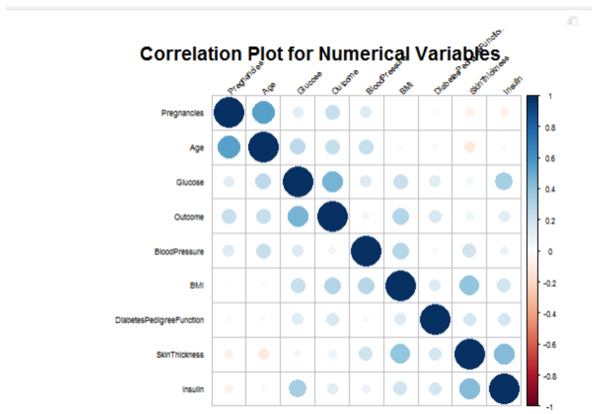

Figure 9 on the Correlation of the variables.

5.3 Algorithms Used

In this, study both models for Decision Tree classification (CART) and KNN were used and the more appropriate model chosen. It is important to note that Since KNN performs on-the-spot learning; it requires frequent database lookups, hence, can be computationally expensive. Decision Tree Classifier does not require such lookups as it has in-memory classification model ready. Since KNN performs instance-based learning, a well-tuned K can model complex decision spaces having arbitrarily complicated decision boundaries, which are not easily modelled by other "eager" learners like Decision Trees.

The main advantage of memory-based approach [the KNN] is that the classifier immediately adapts as we collect new training data. However, the downside is that the computational complexity for classifying new samples grows linearly with the number of samples in the training dataset in the worst-case scenario—unless the dataset has very few dimensions. The decision tree, however, can rapidly classify new examples. Therefore, given the high data availability, quick processing and accuracy needed, the i-Afya system adopted to use the decision tree algorithm. Decision tree are also easier to interpret in terms of representation of data and the complexity.

6 Results and Discussion

6.1 The i-Afya System Results

The logical computation was done using the system computational model and diagnoses done to show whether the patient showed diabetes according to the WHO criteria. The parameters used are real-valued between zero and one, transformed into a binary decision using a cut-off of 0.448. There were 769 training instances in the data set, thus 768 instances and 8 attributes namely Number of Times Pregnant, Glucose Level, Insulin (mu U/ml), Diastolic Blood pressure (mmHg), Skin Thickness measured in mm, Diabetes pedigree function, Age in years and finally the Pedigree Function which translated to the computational loads and efficiency in tree formation. Thus, this model focused on the output of the R libraries and the code implementation using the decision tree algorithm and the k-nearest (KNN) algorithm. The computational model developed using relative comparison of both the KNN and Decision Tree algorithm performances.

The findings from the i-Afya system model is that Blood pressure and skin thickness show little variation with diabetes, as such they can could considered to be little statististical value in the computation. The other variables show average correlation with diabetes, that is the glocuse level, insulin, body mass index and number of pregrancies. The top three most relevant features are "Glucose", "BMI" and Number of times pregnant" because of the low p-values. Insulin and age appear not statistically significant in the model. This was computed using regression analysis.

```
Coefficients:
                          Estimate Std. Error z value Pr(>|z|)
(Intercept)             -8.3461752  0.8157916 -10.231  < 2e-16 ***
Pregnancies              0.1246856  0.0373214   3.341 0.000835 ***
Glucose                  0.0315778  0.0042497   7.431 1.08e-13 ***
Insulin                 -0.0013400  0.0009441  -1.419 0.155781
BMI                      0.0881521  0.0164090   5.372 7.78e-08 ***
DiabetesPedigreeFunction 0.9642132  0.3430094   2.811 0.004938 **
Age                      0.0018904  0.0107225   0.176 0.860053
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 700.47  on 539  degrees of freedom
Residual deviance: 526.56  on 533  degrees of freedom
AIC: 540.56

Number of Fisher Scoring iterations: 5
```

From the prototype model, a classification is derived with the variables with the highest deviance being the root node. The top three most relevant features are "Glucose", "BMI" and Number of times pregnant" because of the low p-values. The classification tree is shown below. This means if a person's BMI less than 45.4 and her diabetes pedigree function less than 0.8745, then she or he is more likely to have diabetes. Decision tree classification implements algorithm for generating a pruned tree. The tree generated CART algorithm can is used for classification problem of whether a patient has tested positive or negative for diabetes. The data mining technique uses the concept of information gain. The output of the decision tree classification is show in figure 10.

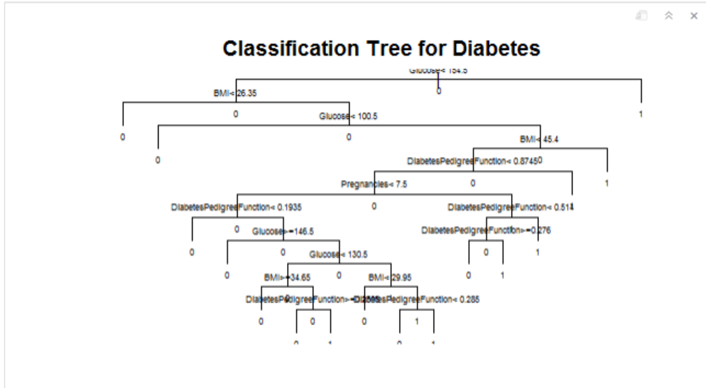

Figure 10

From the table of deviance, we found that adding insulin and age have little effect on the residual deviance. From the statistics and computational model the findings indicate that means if a person's BMI less than 45.4 and her diabetes pedigree function less than 0.8745, then she is more likely to have diabetes.

The i-Afya system model developed in this study is a diabetes self-management system that captures personal information, blood glucose levels, Blood pressure, Physical activities, Insulin dosage and Insulin variables that the patients utilizes during the self-management program. The system allows easy access to the knowledge database history through the graphical user interface (GUI), graphs, and charts for easier understanding of the data. The data is shared among the caregivers of the patient, health institutions and the General Practitioner portal.

7 Discussion

To accurately design a good prediction diagnostics system with a good model it is important to implement accurate and relevant algorithms, which can learn quickly in large data sets, and capture input characteristics. With a good prediction model and an accurate detection technique, diagnosis can be made more efficient for dynamic use of for disease detection tools. Based on the prediction methodology, medical practitioners can envision biomedical diagnosis by engineering tools, which can adapt to any future unexpected conditions automatically. A long-term prediction algorithm can definitely play a very important role in planning and provisioning. Thus, the behaviour of a real time data can be forecasted using machine-learning algorithms such as KNN and Decision tree. Ideally, such processes should be capable of accurately representing the statistical properties of the real data, which is not always possible because of several complex issues. In this research, the use of decision tree for the classification problem proved to be quite accurate and relevant for the study and purpose.

Our findings also show the increasing importance of AI methods for diabetes management. We think these methods will encourage further research into the use of AI methods to extract knowledge from diabetic data. In general, the most striking advances in the application of AI techniques come from data-driven methods that learn from large datasets. The ability to collect information from individual diabetic patients has led to a shift in diabetes management systems; accordingly, systems that lack access to valuable data will face substantial hurdles. Diabetes management will be geared towards tailored management therapies, at the level of smaller strata of patients or even individuals. Thus, management systems provided to diabetic patients should be tailored to address their needs at various points during their illness.

This study was able to confirm the positive effect of using a digital system for diabetic's diagnostics and management. The research showed that technology solutions for enhancing treatment of diabetes have a net positive effect on the treatment outcomes. The clinical decision support capabilities used in the system shows that the i-Afya intelligent computational power can be harnessed to provide data analytics for enhanced management of diabetes patients in Kenya.

The limitations of this study include not analyzing the long-term effects of the use of the i-Afya system and the selection bias of the subjects. This can be done by having more resources and timelines to implement the system across the country at public facilities. However, this study still has great significance in that the statistically significant positive changes in the clinical course of diabetes, which were displayed among users of the widely available application.

8 Conclusion

One of the important real-world medical problems is the detection of diabetes at early stage. In this study, systematic efforts were made in designing and implementing a system, which could result in the accurate detection and prediction of a disease like diabetes. The study thus successfully showed the application of the decision tree and KNN algorithms in disease diagnosis and the subsequent computation of large diabetes datasets to provide the correct solution. This study also revealed that the i-Afya Intelligent System resulted to a high level of user satisfaction and had a positive effect on diabetes management were it to be was used within the Kenyan health system. This has the potential to ultimately improve the treatment outcomes as well as lowering the cost of treatment, access and management of diabetes in Kenya.

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