An expert system for early diagnosis of stroke

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The rate at which stroke is killing humans globally on a daily basis is becoming worrisome. Stroke is a medical emergency that needs prompt attention because it stops the supply of blood to the brain. Early detection of the disease depends on the approach/method utilized in diagnosing this disease. As such, a suitable method that can accurately detect it becomes a compelling alternative to overcome the challenges peculiar to the disease. An expert system for early diagnosis of stroke is proposed to ameliorate the challenges because it is an intelligent system that can aid physicians in managing the uncertainties associated with stroke and aid early diagnosis. This paper presents an expert system for early diagnosis of stroke that uses the human-like reasoning style, a Fuzzy Logic system to diagnose and suggest possible treatments for stroke through interactivity with user, with aim of developing an expert system and exploring the potential of fuzzy logic to assist clinicians in Nigeria to accurately predict and differentiate between the different types of stroke. It employs programs like MySQL, PHP, JAVA and XML. The system provides adequate and appropriate results and also makes reliable predictions to users.

Key words: Stroke, expert system, fuzzy logic, diagnosis, intelligent.

INTRODUCTION

In most cases, a single symptom may be indicative of several different diseases and it is not easy to follow a particular path of diagnosis without any mistake (Sikchi et al., 2013). In view of these and many challenges faced in clinical care, many researchers have constructed various support systems know as Clinical Decision Support Systems (CDSSs) with Artificial intelligence principles to ensure an accurate and timely medical delivery. A CDSS is more specifically defined as a program or software created to help clinicians reach decisions with better accuracy (De et al., 2011). CDSS provides support to clinicians on various stages involved in the care process. The stages are from preventive care through diagnosis and treatment to monitoring then follow-up.

Stroke is the utmost important single cause of severe incapacity in adults and the next most common cause of death after coronary heart disease. In developing countries, increased life expectancy has modified the pattern of cause-specific mortality, with a higher burden of cardiovascular diseases (WHO, 2003). The significance of stroke in low-income and middle-income (developing) countries has recently become better appreciated and highlighted by the recently updated estimate from the global burden of disease study, which shows that over 80% of all stroke death occurs in middle-income and low-income regions of the world (Kolapo et al., 2000). Stroke populations has varied from 0.9 to 4.0%, whereas among neurological admissions stroke accounted for 0.5-45% (Ojini et al., 2003). At

Lagos University Teaching Hospital (LUTH), stroke is the most common cause of neurological admission(Ojini et al., 2003). Furthermore, in sub-Saharan Africa, many of the hospital reported a high risk of death from stroke with more than 30% of patients dying within the 1st month of onset of stroke (Ogun et al., 2005). A recent review study in south-south of Nigeria, show an in-hospital mortality rate of 7.8% (Ansa et al., 2012).

Stroke is a global pandemic, affecting both developing and developed countries. In Nigeria, a steady rise in affected patients is becoming noticeable to all which inspired the development of this research. Stroke is instigated by smoking cigarettes, high blood pressure, history of stroke as regards the family, high cholesterol, diabetes, obesity, overweight and cardiovascular diseases which disturb the brain and damage some part of the body (legs, hand) coordinated by that portion of the brain. The symptoms of stroke vary from emotionlessness of the affected body part to low speech recognition and loss of balance (Obi et al., 2011). Expert systems are one of the recognized fields in artificial intelligence (Alma et al., 2014) that has been applied to a number of systems, apparently for different reasons. It focuses on heuristic decision making and rules, generally as manifested in “if - then’" rules, possibly employing weights on the rules to capture uncertainty or ambiguity.

REVIEW OF RELATED LITERATURE

Stroke is defined as sudden onset of a focal neurological shortfall lasting more than 24 h. It is also called Apoplexy or Cerebrovascular Accident (CVA). An acute stroke refers to the first 24-h period of a stroke. While focal neurological deficit lasting below 24 h (usually 5-20 min) known as Transient Ischemic Attack (TIA) is relevant but beyond the range of this project.

Acute stroke basics

A stroke results from sudden decrease of blood movement to the brain which causes rapid loss of ability to function effectively. Its symptoms, including hemiparesis, vomiting, drowsiness, and loss of consciousness, often go unrecognized as a stroke until after the acute treatment window has passed. Stroke causes a high burden of death and disability, both in Nigeria and around the world. Stroke is classified mainly on the basis of its aetiology as either one of ischaemic (87%) or haemorrhagic (13%). Ischaemic stroke is produced by blocking of a cerebral artery [thrombotic or atherosclerotic (50%), micro artery occlusion, “lacunar stroke”, (25%) and embolic (25%)]. (Azarpazhooh et al., 2008). Hemorrhagic stroke is caused by spontaneous separation of blood vessels or aneurysms or secondary to trauma (Hemphill et al., 2015).

Investigation of a stroke

MR or CT angiography demonstrate the cerebral vasculature and may add further information such as aneurisms, segmental narrowing or complete blockage of blood vessels. Doppler ultrasonography of carotid and vertebral vessels in the neck add further information- and is particularly useful in recommending patient for endarterectomy endovascular procedure or intravascular thrombolysis treatment. One analysis found that the immediate and long term success of thrombolysis is correlated with the site of occlusion as determined by Doppler ultrasonography (Saqqur et al., 2007).

Assessment of acute stroke

The evaluation and treatment of patients with acute ischemic stroke should be performed without delay. The general and neurological history, together with brain imaging, provide with thrombolytic agents. Brain imaging is currently mandatory to guide acute intervention. The intervention protocols for hemorrhagic stroke are different from ischemic stroke, and fatal complications may result from misdiagnosis. Other clinical and para-clinical tests required are not discussed here (Adams *et al*., 2003).

Risk factors of stroke

(i) Age: The older a man is, the greater his risk of stroke. The chances of having a stroke more than double every 10 years after age 55. More than two - thirds of strokes identified involve people over 65.

(ii) Family history: Having a close family member with heart disease or a stroke history increases your own stroke risk. Genetic factors influence blood coagulation and the development of atherosclerosis or high blood pressure, all of which have impact on the risk of stroke. Aneurysms and arteriovenous deformities, are two conditions that affect hemorrhagic strokes, which definitely have a genetic basis. But genes are not the sole explanation for the increased risk of stroke. Relatives may also share eating habits and other behaviors that can promote strokes.

(iii) Ethnicity: Race is another risk factor. African Americans, e.g, are nearly twice as likely to suffer a stroke as whites. The relative importance of genes versus lifestyle in causing this increased risk is uncertain.

(iv) Previous stroke or TIA: Anywhere from 5 to 14% of people who have one stroke will have another within a year. And up to 40% of people who have had a TIA will go on to have a stroke at some point.

(v) Heart problems: About 3 to 4% of persons who have a heart attack go on to have an ischemic stroke. People with atrial fibrillation, a type of abnormal heartbeat, are also at increased risk of stroke.

(vi) High blood pressure: Left untreated, high blood pressure damages the blood vessels so much that it is the one of the leading risk factors for all sorts of strokes, roughly doubling your lifetime risk. Fortunately, treating high blood pressure, or avoiding it in the first place, helps bring this risk back down.

(vii) Smoking: Smoking doubles the risk of ischemic stroke and quadruples the risk of hemorrhagic stroke. Smoking also contributes too many of the other stroke risk factors: it raises blood pressure, reduces the level of beneficial HDL cholesterol, damages the protective lining of the blood vessels, and makes blood more prone to clot. Exposure to other people's tobacco smoke also substantially increases the risk of stroke.

(viii) Unfavorable cholesterol profile: Abnormal cholesterol levels in particular, high LDL: increase your risk of stroke, even if you have no other risk factors for heart disease. At the same time, lowering your LDL helps to reduce your risk of stroke.

(ix) Physical inactivity: Lack of exercise, which is directly linked to an increased risk of heart disease, also contributes to obesity and other risk factors for stroke. The benefits of exercise include making blood less likely to clot, controlling weight, lowering blood pressure, and increasing levels of protective HDL cholesterol.

(x) Obesity and overweight: Being overweight increases stroke risk as well as risk for heart disease. Excess pounds strain the entire circulatory system and predispose you to other stroke risk factors such as high blood pressure, high cholesterol, and diabetes.

(xi) Diabetes: If you have diabetes, your odds of having an ischemic stroke are several times greater than those of people without the disease. Diabetes increases the tendency of the blood to form clots, which can dam up the arteries.

How to reduce your risk of stroke

(1) Keep your blood pressure within healthy limits.
(2) Keep your cholesterol in check.
(3) Kick the smoking habit to the curb.
(4) Watch your weight.
(5) Become physically active.

Fuzzy logic expert systems

Fuzzy logic expert system is a group of membership function and rules. These function and rules are used to reason about data. Fuzzy expert system is oriented towards numerical processing. It takes number as input, and then translate the input numbers into linguistic terms like large, medium and small. Then the task of rules is to map the input linguistic term into comparable linguistic terms describing the output. Finally, the translation of output linguistic terms into an output number is complete (Kadhim et al., 2011).

Medical expert system

A huge figure of expert systems is medical. The main aim of most medical expert system is

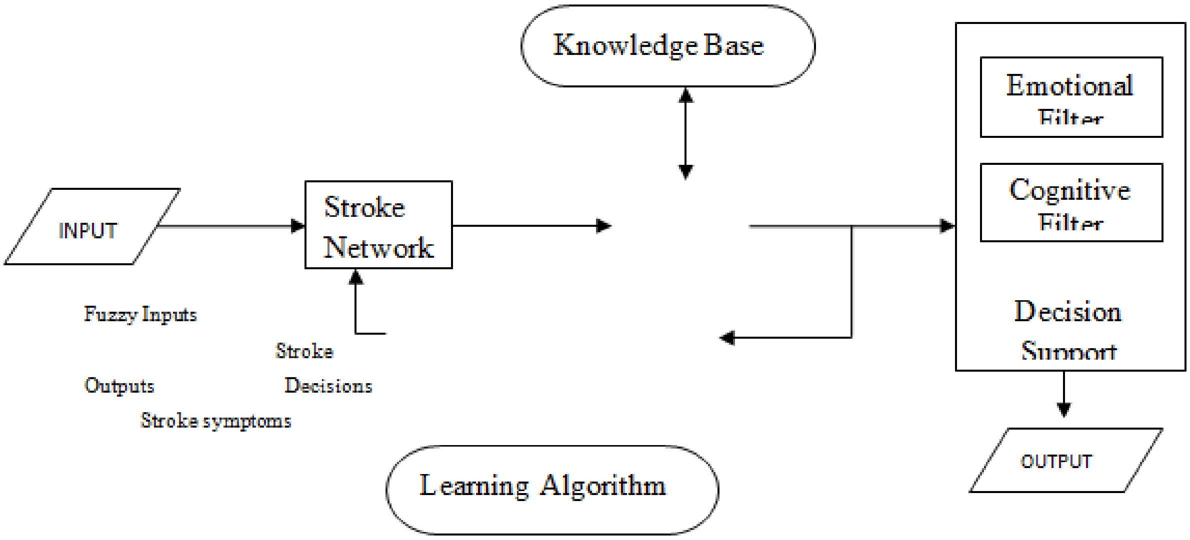

Figure 1. Proposed fuzzy logic system for stroke diagnosis.

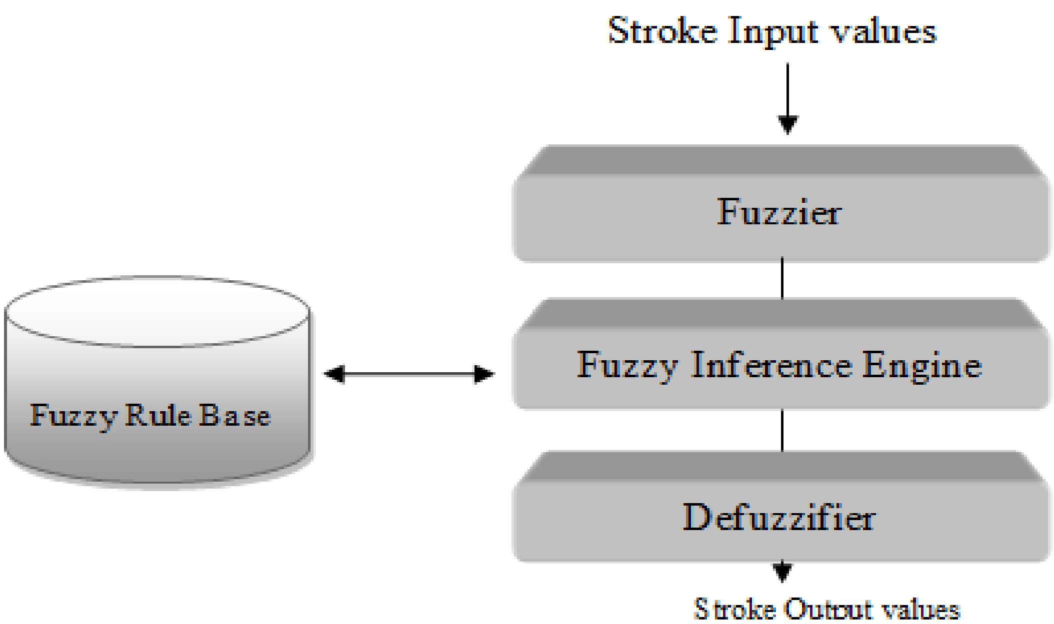

Figure 2. The general architecture of the fuzzy logic inference engine.

identification and cure of diseases. A medical expert system comprises of programs and medical knowledge base. The information obtained from medical expert system is similar to the information given by proficient in that particular area (Singla, 2013). The system design and development process are shown in Figure 1 and 2. Above.

Working of medical expert systems

Table 1 show the classification of input variables.

Theoretical framework

Kadhim et al. (2011) build up a fuzzy expert system for judgment of back pain diseases based on the experimental examination symptoms using fuzzy rules. The user has to key in parameters such as body mass index, age, gender of 8 patient and experimental examination symptoms for this fuzzy expert system.

Pachpande et al. (2018) planned and put into operation a medical expert system for the diagnosis of some pulmonary disorders. One of the endings accomplished throughout the route

Table 1. Classification of input variables.

Input variable	Range	Fuzzy Sets
Age	<25	Young
	22-40	Middle
	38>	Old
BMI	<18	Low
	19-25	Medium
	24>	High
Symptom	<20	Low
	18-60	Medium
	58-80	High
	78>	Very high

Source: Kadhim et al. (2011).

of this research was that the process of knowledge acquisition is a continuous process and for this reason an expert system cannot be made in a single pass fashion – an incremental approach is certain. Tables 2 and 3 shows various diseases diagnosed in expert systems.

Table 2. Diseases diagnosed in expert system.

S/N	Name of disease
1	Meningitis
2	Cerebral palsy
3	Migraine
4	Cluster headache
5	Stroke
6	Epilepsy
7	Multiple sclerosis
8	Parkinson
9	Alzheimer
10	Huntington disease

Source: Al-Hajji, (2012).

METHODOLOGY AND SYSTEM DESIGN

System design is how the overall system architecture can be determined which consists of a set of physical processing components, hardware, people, and the communication among them that will satisfy the system's essential requirements (Alan et al., 2012). In general, this will decides how the new system will be built.

Data collection

The data collection includes the case records of all patients admitted into the medical wards of a 300-bed specialist's hospital in Benin City. The cases were admitted over a five-year period covering 2013 to 2018. We recorded details of history and clinical examination used to diagnose and classify stroke.

In order to train the FL expert system, a dataset of 200 previously diagnosed stroke cases was collected from Central Hospital, Benin city, Edo state, Nigeria. This comprised of 120 female and 80 male of 20 to 60 years old years and weight between 45 and 90 kg. This was confirmed by a group of five medical practitioners with average of 15 years of practice experience. In this sequel, an honest attempt to incorporate fuzzy approach was used and we developed a web-based fuzzy expert system for the management of stroke. In order not to leave the system design incomplete, for logical modeling, Unified Modeling Language (UML) was used in order to achieve a concise and systematic modeling. For physical modeling, the system was developed using PHP as a scripting language with MySQL relational database on Apache Sever under windows operating system platform, Java Script, and HTML to archive the system design.

Logical system modeling

UML is an object oriented tool, used to capture and model some of the functionalities in the system. UML is an excellent tool for modeling objects and the relationship between the objects and classes.

Physical system design

The proposed system consists of three modules: the patient module, medical repository module and the fuzzy rule base module. The software modules are developed using PHP as a scripting language with MySQL relational database on Apache Sever under windows operating system platform, Java Script and HTML to archive the system design. Web services are used to exchange data between the software components and the patient. The message exchange has been implemented through Simple Object Access Protocol (SOAP). Both the medical expert and the patient can call the knowledge-base. Figure 3 shows the models of Proposed Fuzzy Logic System for Stroke Diagnosis, indicating how the input in this case the stroke symptoms must be fed

Table 3. Shows the results of the 100 patients who were monitored and classified in the classifier optimizer.

Patient	Classifiers	Fuzzy percentage	Types of stroke
1	CT Scan	62.5	Ischemic
2	High Cholesterol	64.4	Ischemic
3	Hypertension	72.3	Ischemic
4	Diabetics	84.6	Ischemic
5	CT Scan	62.5	Hemorrhagic
6	Hypertension	70.2	Ischemic
7	Hypertension	83.4	Ischemic
8	Hypotension	10.2	Ischemic
9	Obesity	36.6	Ischemic
10	BMI	54.5	Hemorrhagic
11	High Cholesterol	61.5	Ischemic
12	Hypertension	70.2	Ischemic
13	Hypertension	79.3	Ischemic
14	Hypertension	84.2	Ischemic
15	Normal	52	Normal
16	High Cholesterol	64.4	Ischemic
17	Hypertension	70.5	Ischemic
18	Hypertension	83.2	Hemorrhagic
19	Diabetics	88.6	Ischemic
20	Hypertension	81.8	Ischemic
21	Diabetics	82.8	Ischemic
22	Diabetics	88.1	Ischemic
23	Hypertension	74.5	Ischemic
24	Diabetics	88.5	Ischemic
25	Diabetics	88.6	Ischemic
26	CT Scan	62.5	Hemorrhagic
27	High Cholesterol	64.4	Ischemic
28	Hypertension	81.8	Ischemic
29	Hypertension	81.7	Ischemic
30	Obesity	61.3	Ischemic
31	High Cholesterol	62.5	Ischemic
32	Hypertension	74	Ischemic
33	Diabetics	84.3	Ischemic
34	High Cholesterol	61.3	Ischemic
35	CT Scan	71.8	Ischemic
36	CT Scan	83.2	Ischemic
37	Hypertension	10.2	Ischemic
38	Obesity	36.6	Hemorrhagic
39	Normal	55.2	Ischemic
40	Obesity	60.8	Ischemic
41	High Cholesterol	71.8	Ischemic
42	Hypertension	79.3	Ischemic
43	Diabetics	84	Ischemic
44	Normal	52	Hemorrhagic
45	Obesity	56.9	Ischemic
46	High Cholesterol	66.4	Ischemic
47	Hypertension	82.9	Ischemic
48	Diabetics	87.8	Ischemic
49	Hypertension	81.6	Ischemic
50	Diabetics	82.6	Ischemic
51	Diabetics	87.4	Ischemic
52	Hypertension	75.8	Ischemic
53	Diabetics	87.7	Ischemic
54	Diabetics	87.8	Ischemic

Table 3. Continue

55	High Cholesterol	59.7	Ischemic
56	CT Scan	65.2	Ischemic
57	Hypertension	73.8	Ischemic
58	CT Scan	81.6	Ischemic
59	Diabetics	77.8	Ischemic
60	Hypotension	10.2	Ischemic
61	Obesity	36.6	Ischemic
62	BMI	54.5	Hemorrhagic
63	High Cholesterol	61.5	Ischemic
64	Hypertension	70.2	Ischemic
65	Hypertension	79.3	Ischemic
66	Hypertension	84.2	Ischemic
67	Normal	52	Normal
68	High Cholesterol	64.4	Ischemic
69	Hypertension	70.5	Ischemic
70	Hypertension	83.2	Hemorrhagic
71	Diabetics	88.6	Ischemic
72	Hypertension	81.8	Ischemic
73	Diabetics	82.8	Ischemic
74	Diabetics	88.1	Ischemic
75	Hypertension	74.5	Ischemic
76	Diabetics	88.5	Ischemic
77	Diabetics	88.6	Ischemic
78	CT Scan	62.5	Hemorrhagic
79	High Cholesterol	64.4	Ischemic
80	Hypertension	81.8	Ischemic
81	Hypertension	81.7	Ischemic
82	Obesity	61.3	Hemorrhagic
83	High Cholesterol	62.5	Ischemic
84	Hypertension	74	Ischemic
85	Diabetics	84.3	Ischemic
86	Obesity	90.65	Hemorrhagic
87	High Cholesterol	98.7	Ischemic
88	Hypertension	61.75	Ischemic
89	Diabetics	44.8	Ischemic
90	Obesity	85	Ischemic
91	High Cholesterol	90	Ischemic
92	Hypertension	95	Ischemic
93	Diabetics	47	Ischemic
94	Obesity	55.05	Hemorrhagic
95	High Cholesterol	63.1	Ischemic
96	Hypertension	71.15	Ischemic
97	Diabetics	79.2	Hemorrhagic
98	Obesity	87.25	Ischemic
99	High Cholesterol	95.3	Ischemic
100	Hypertension	83.35	Ischemic

Source: Field Work (2019).

into the fuzzy network to yield a particular output. This output is automatically sent into the fuzzy inference engine for decision making. If decisions made by the Fuzzy system is not as desired.

IMPLEMENTATION

This provides the practical aspect of Fuzzy Expert system. It consists of the requirement analysis, implementation and result analysis of the prototype Fuzzy system for stroke risk factors,

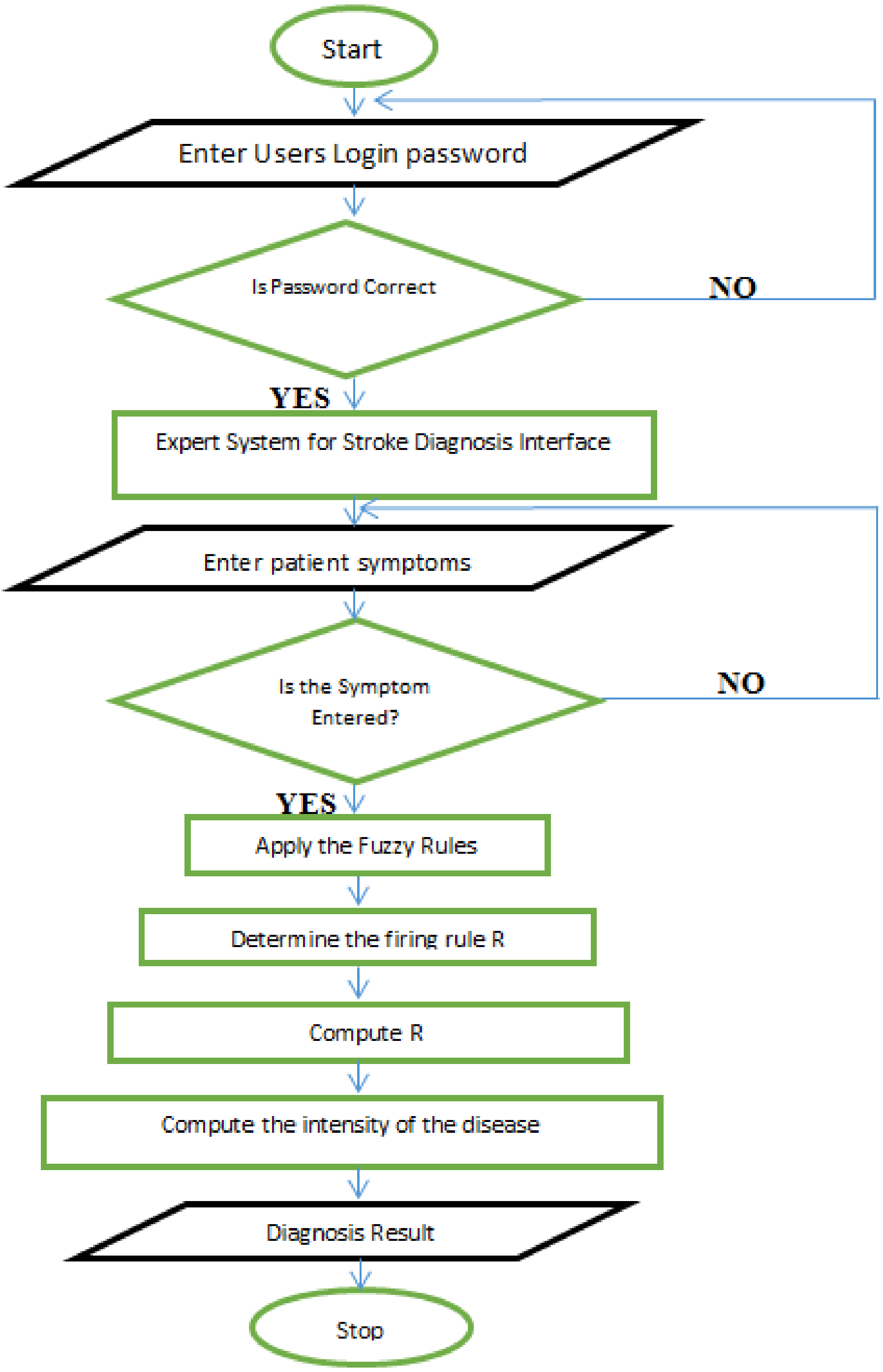

Figure 3. Flowchart of fuzzy system.

stroke confirmations and complications of stroke. This is achieved by transforming the information from the system specifications component analysis reported in chapter three. This system can effectively capture patients' symptoms from the patient or family of the patient and accurately classify the patients' degree of infections. Also incurred are the system capability and deployment criteria, system impacts and benefits as well as system vulnerability and threats. The implementation process is shown from Figure 3 to 7.

Simulation results of the proposed method

Table 3 show the results obtained for 100 patients, and based on these results we obtain the classification accuracy rate and classification error rate, for which we use the following equations:

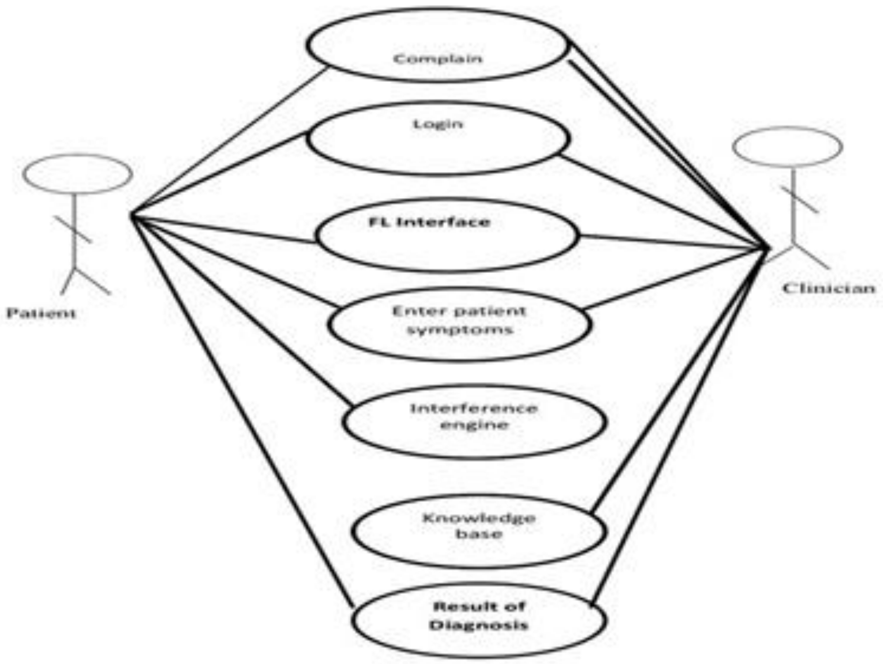

Figure 4. Use case diagram of the proposed system.

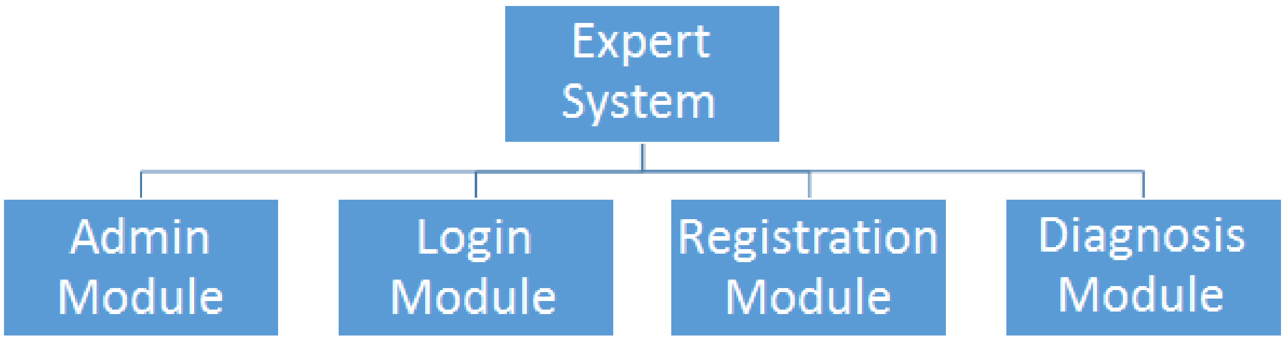

Figure 5. Block diagram of system module.

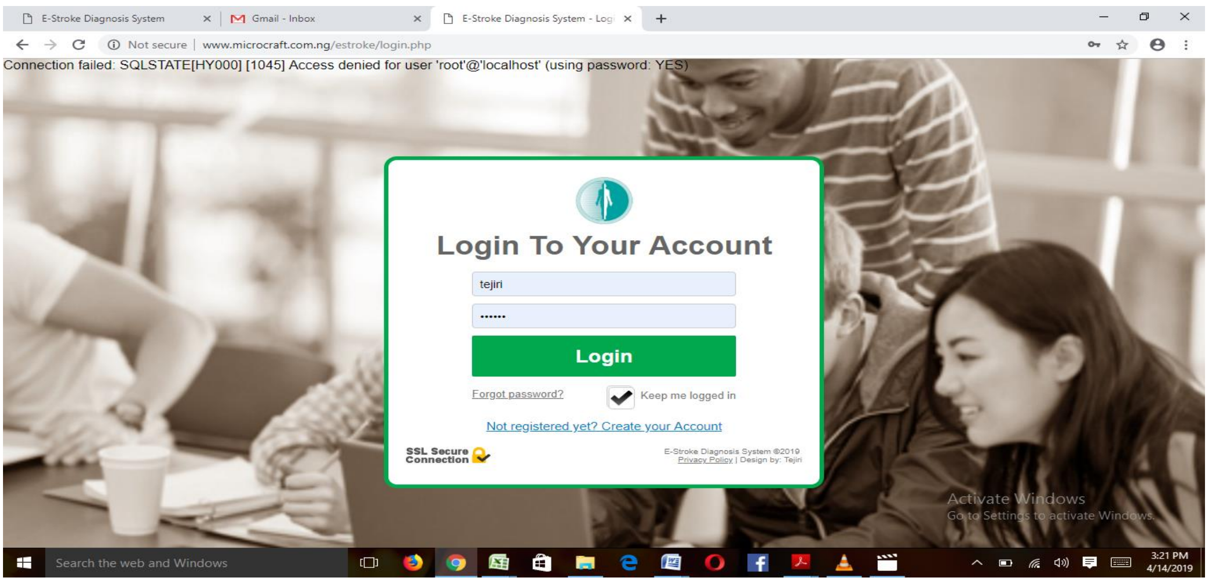

Figure 6. Login page.

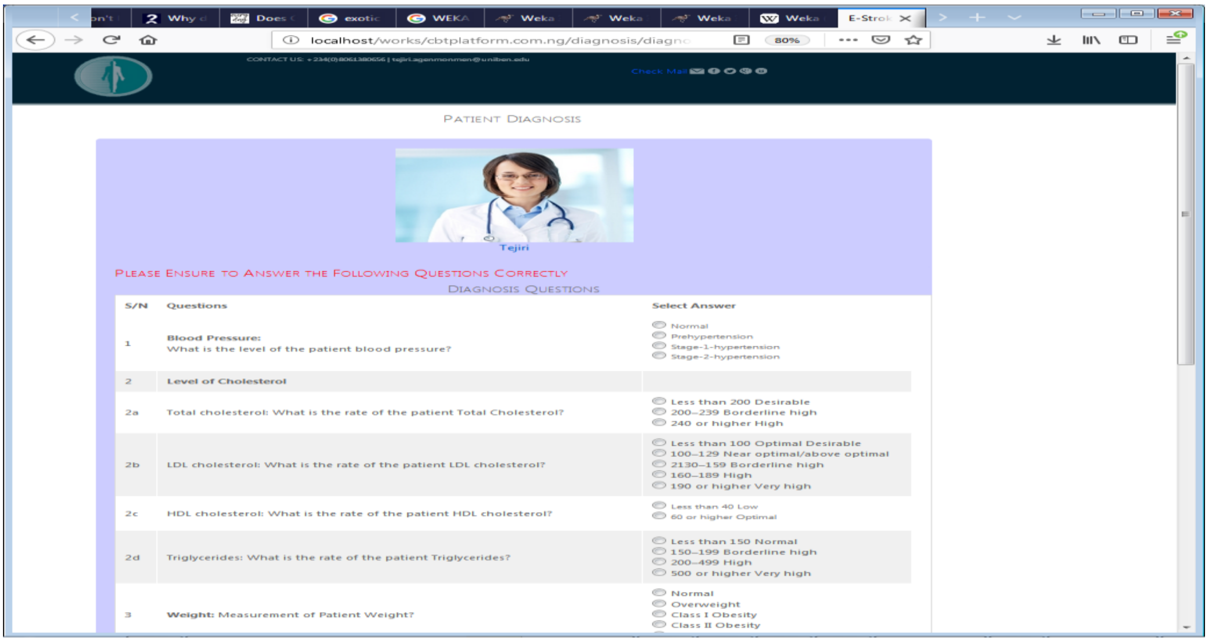

Figure 7. Print screen of the diagnosis test question for stroke page.

The Classification Accuracy Rate (CA) is calculated as follows:

$$CA = \frac{N_c}{N_t} \qquad (1)$$

Where;

N_c is the Number of Training Instances Correctly Classified

N_t is the Number of Training instances.

The Classification Error Rate (CE) is calculated as follows:

$$CE = \frac{N_e}{N_t} \qquad (2)$$

Where;

N_e is the Number of Training Instances Incorrectly Classified

N_t is the Number of Training instances.

We therefore, performed experiments using 24 h monitoring of 100 patients, from which the trend was obtained which was the one that entered to the fuzzy classifier, which produces the following results based on the accuracy rate in the classification of 100 patients, an accuracy rate of 80% was obtained, which classified 24 of 100 patients correctly based on the result given by the Type of Stroke and give us a classification error rate of 20%, which is equivalent to 6 of 1000 in-correctly classified. Table shows a summary of the results. The data gathered were classified using the fuzzy expert system that is optimized with the genetic algorithm. Of the 100 patients who were monitored, the classification with 14 rules given by an expert, the result was: accuracy rate of 90% with a 10% error, this is shown in Table 3.

Conclusion

The paper presents a comprehensive analysis of fuzzy logic system; it is a smart system for stroke diagnosis which helps to provide an early diagnosis of the presence of stroke. This newly developed model uses a Fuzzy Expert System technique which is implemented by using a human reasoning set of decision rules for the study of stroke. This method takes less time and is more accurate for classifying the types of stroke. The system helps health workers, most especially in developing countries, who do not have enough specialists for stroke like Cardiologists, internists etc. The system provides a better opportunity at the start of pharmacological management and dietary hygiene measures; it also provides an informed medical list of stroke symptoms authenticated by doctors who are active practitioners in the field.

RECOMMENDATIONS

We recommend the following:

(i) The system can run on mobile devices and taken to remote locations where suitable power supply is a challenge.
(ii) The system can be ported into mobile devices; this will increase accessibility of the model.
(iii) Government at different level should provide a means where the system can be made available to the populace.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

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