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E-model for Early Detection of Breast Cancer and Patient Monitoring

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Abstract:- Breast cancer is becoming one of the most common diseases among women and is a growing global concern. A significant number of women have died worldwide from breast cancer. Studies suggest that early detection gives one better chance at treatment and management. However, the major challenges in early detection of breast cancer are awareness issues and patients' insensitivity about the disease. This implies that regular breast examination leads to early detection of signs and symptoms of breast cancer. This exercise has been challenged with awareness, improper ways of conducting it and reporting of signs and symptom to appropriate quarters. This work is aimed at designing and development of a computer assisted system that runs on both desktop and mobile device(s) to assist women in conducting self-breast examination. To achieve this, object oriented analysis and design methodology (OOADM) was adopted for investigation and implementation. This work was designed and implemented in Microsoft Visual Studio while MySQL was used as the database management (DBMS). The rule-based approach was used for classification of breast abnormality. The result is an eHealth information system for early detection of breast cancer and patient monitoring. This will assist women to properly conduct self-breast examination, upload signs and symptoms discovered and enable medical professionals monitor patients.

Keywords:- *Cancer, Fibrosis, Mastectomy, Lymph Nodes, Oncology, Mammography, Telemedicine, Receptor.*

I. INTRODUCTION

A high level of care coordination and patient involvement are necessary for the effective management and treatment of cancer throughout the care continuum. Cancer is a complex disease with a variety of treatment options necessitating patient education and understanding to make appropriate care decisions (California Health Foundation, 2012). Patients may be asked to provide information regarding previous medical interactions as they move from diagnosis to treatment to survival. Throughout their care, patients frequently see many doctors. Patients often have debilitating physical, mental, and emotional side-effects from treatment, which they must manage while adhering to complex medicine and chemotherapy schedules.

The second most common cause of cancer-related mortality for women and the most often diagnosed cancer is breast cancer. About 230,480 women received a breast cancer diagnosis in 2011, and 39,520 of them lost their lives to the illness. Beginning in 2000, the incidence of female breast cancer started to reduce. Between 2002 and 2003, there was a notable 7% decrease in incidence, which was ascribed to fewer women utilizing Menopausal Hormone Therapy (MHT). From 2004 to 2008, rates stayed constant. On the other hand, the death rate from breast cancer has been steadily declining. Between 2004 and 2008, the annual drop in the number of women 50 years of age and older was more than two percent, largely attributable to earlier detection and better treatment. Over the same time span, the death rate for women under 50 has decreased by 3.1% per year. Biological factors including age, family history, high breast tissue density, and others can increase a woman's chance of developing breast cancer. Modifiable risk factors, such as obesity, lack of physical activity, and alcohol consumption have also been linked to breast cancer (Kösters and Gøtzsche, 2003).

Since the introduction of information and communication technology (ICT) into the healthcare sector, notable advancements in health and quality of life have been made possible. Health technology is used to delay the start of sickness, lower the chance that it will occur, and lessen its effects. It supports the diagnosis of clinical indicators for identifying the kind and source of pathological events and aids doctors in screening for abnormalities. Moreover, technology

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is expected to reduce mortality and morbidity rates, to shorten illness duration, to improve the quality of care (also increasing access to it), to reduce the relapse risk, and to limit the decay of a person's activities/functionalities which correspond to an increase in life expectancy (Rizzi et al., 2012).

II. LITERATURE REVIEW

Harbeck et al (2019) opined that breast cancer is the most malignancy in women worldwide and is curable in 70-80% of patients with early stage, non-metastatic disease. They noted that advanced breast cancer with distant metastases is considered incurable. They noted that breast cancer is a heterogeneous disease. They noted that treatment strategies differ according to molecular subtype. They advised that future therapeutic concepts should aim at individualization of therapy as well as treatment de-escalation and escalation based on tumor biology and early therapy response. They observed that worldwide access to therapeutic advances is a global challenge in breast cancer care for the future.

Anooj (2011) worked on clinical support system by checking the risk level prediction of heart diseases using weighted fuzzy rules. The researcher obtained data from different sources and made evaluations based on computer based application. The researcher deviated from creating a knowledge base from experts. He argued that the process is time consuming and that the expert's opinion could be subjective. Therefore, machine learning technique was developed to gain knowledge automatically from examples or raw data. Then a weighted fuzzy rule based clinical support system is presented for the diagnosis of heart disease, automatically obtaining knowledge from the patient's clinical data. The clinical support system for the risk prediction of heart patients consists of two phases; automated approach for the generation of weighted fuzzy rules and developing a fuzzy rule based decision support system. The weighted fuzzy rules were obtained using mining technique, attribute selection, and attribute weightage method to obtain the weighted fuzzy rules. Then, the fuzzy system is constructed in accordance with the weighted fuzzy rules and chosen attributes. Finally, the datasets for the work was got from UCI repository and the performance of the system was compared with the neural network based system utilizing accuracy, sensitivity and specificity.

➢ *Clinical or Self Breast Exam*

A clinical or self-breast include feeling for lumps or other irregularities on the breast. Clinical breast examination is conducted in the clinic/hospital by medial professional while breast self-examination is conducted by the individual. Meanwhile, both adopt the same methods or steps. Medical evidence, however, does not support its use in women with a typical risk for breast cancer (Kösters and Gøtzsche, 2003).

Breast examination (either clinical breast exams (CBE) by a health care provider or by self-exams) were once widely recommended. They however are not supported by evidence and may, like mammography and other screening methods that produce false positive results, contribute to harm. The use of screening in women without symptoms and at low risk is thus controversial (Saslow et al.,2004).

A 2003 Cochrane review found screening by breast self-examination or by clinical exam is not associated with lower death rates among women who report performing breast self-examination and does, like other breast cancer screening methods, increase harms, in terms of increased numbers of benign lesions identified and an increased number of biopsies performed. They conclude "screening by breast self-examination or physical examination cannot be recommended" (Kösters and Gøtzsche, 2003).

➢ *Mammography*

Mammography is the process of using low-energy X-rays (usually around 30 kVp) to examine the human breast and is used as a diagnostic and a screening tool. The goal of mammography is the early detection of breast cancer, typically through detection of characteristic masses and/or micro calcifications. The use of mammography in universal screening for breast cancer is controversial for not reducing all-cause mortality and for causing harms through unnecessary treatments and medical procedures. Many national organizations recommend it for older women. If screening mammography (as opposed to diagnostic mammography, which is used in a woman with symptoms that suggest breast cancer) is chosen for women at normal risk for breast cancer, it should only be done every two years in women between the ages of 50 and 74 (Schonberg, 2010).

III. METHODOLOGY

The Object Oriented Analysis and Design Methodology is used in this work to describe the actors and use cases found in the E-Health Information system. Each use case is covered in detail with diagrams and tables in the module section in which it is found. The functional requirements are divided into two main modules: the patient and medical personnel (MP) or doctor.

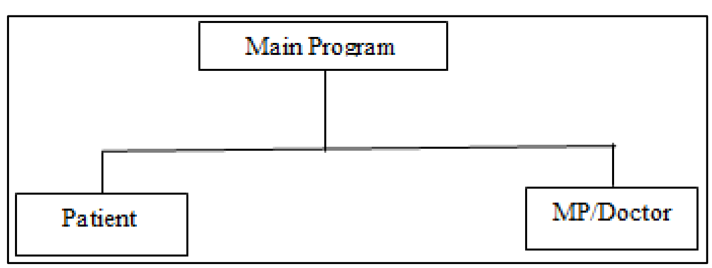

Fig 1: The Main Menus of the System

❖ *Menus and Sub-Menus of the New System*

The new system has two menus – Medical Personnel and Patient as shown in figure 1. The Medical Personnel module (menu) has the following sub-menus as shown in figure 2 while the Patient module (menu) has the following sub-menus as shown in figure 3.

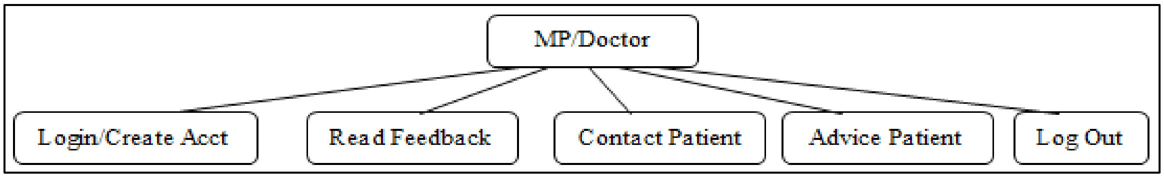

Fig 2: Sub-Menus of the MP/Doctor Module (Menu)

- **Login/Create Acct.:** This menu helps the MP to login to the system or create a new account.
- **Read Feedback**: The feedbacks from the patients are read by the medical professional.
- **Contact Patient**: If need be, the patients are contacted through the contact information provided by them during registration.
- **Advice Patient**: After thoroughly scrutinized the feedback prom the patients, medical professional can advise the patient from distance.
- **Log Out**: This logs the user out when he/she is done with the system.

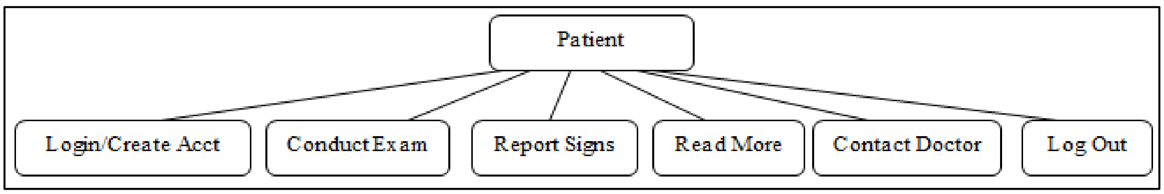

Fig 3: Sub-Menus of the Patient Module (Menu)

- **Login/Create Acct:** This menu helps the patient to login to the system or create a new account.
- **Conduct Exam:** After successful registration of patient, she can use this menu to perform breast self-examination. The procedures/methods are attached in this module to enable them (especially novice) to perform appropriate examination.
- **Report Signs:** When a patient has successfully conducted the examination, she can upload/report her signs which would be sent to the central database.
- **Read More:** This module enables the patient to red and research more about breast cancer and other related matters.
- **Contact Doctor:** Patients can contact doctors if necessary using this module.
- **Log Out:** This logs the user out when he/she is done with the system.

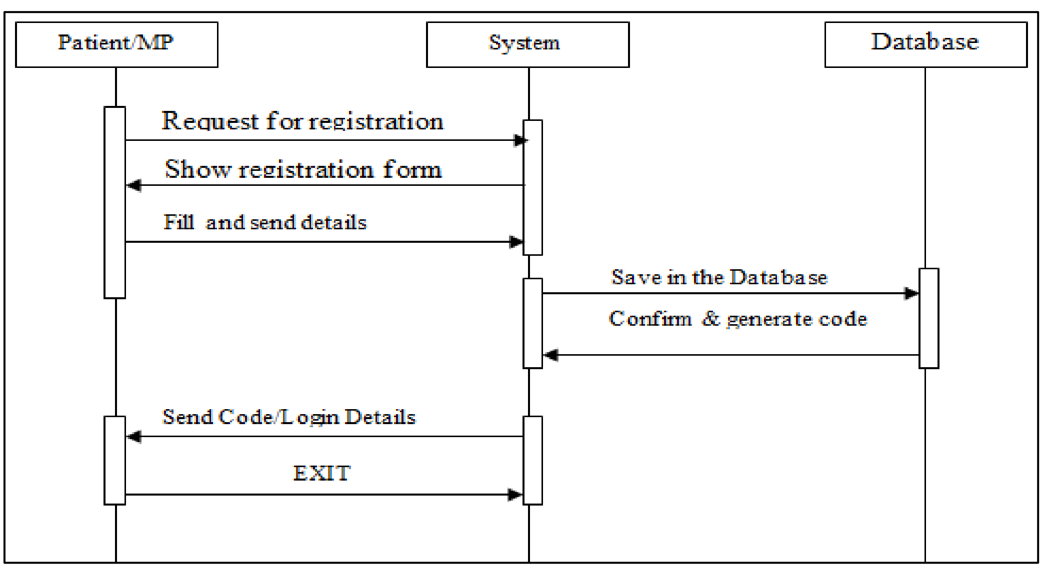

Fig 4: Sequence Diagram for Account Creation

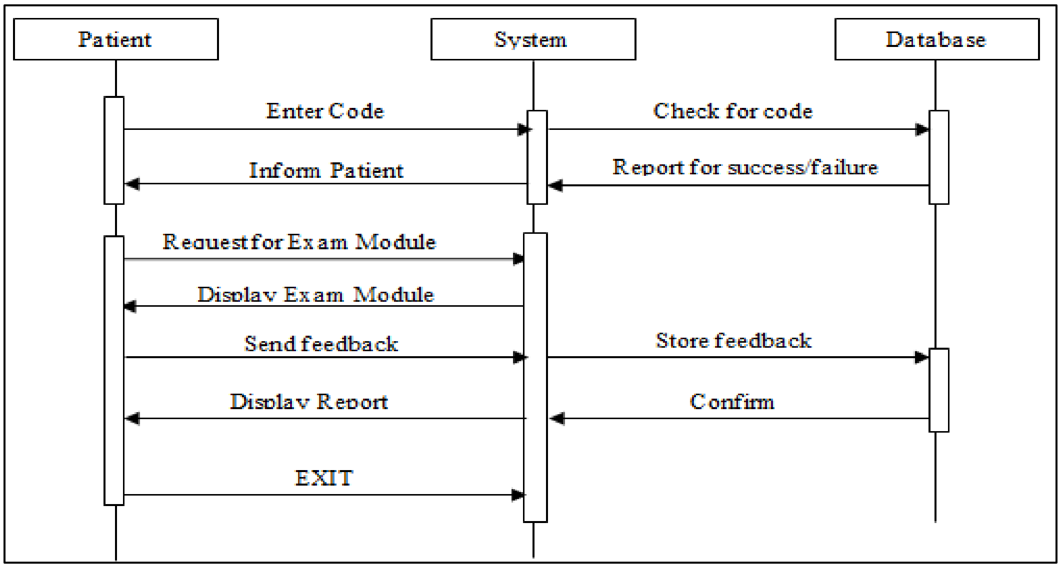

Fig 5: Sequence Diagram of How to Perform the Exercise

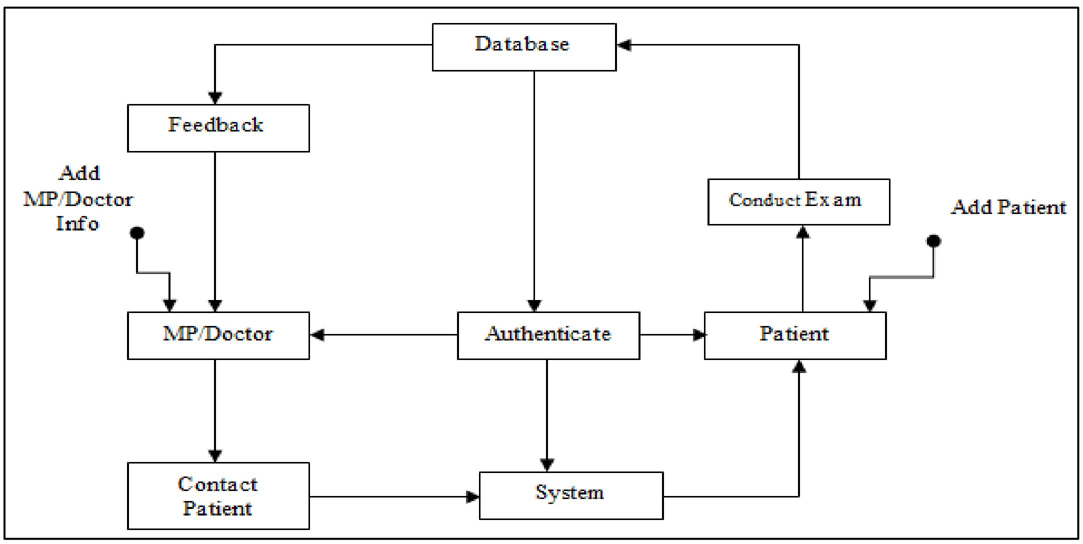

Fig 6: Components Diagram of the New System

IV. CONCLUSION

This work implemented an e-model for health information system is a system that is capable of helping one detect and eventually treat breast cancer on early detection. It makes provision for easy access to vital medical assistance information, timely response and feedback as it is also available on mobile phones, as well as a medium of sensitization for the general public.

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