SMART OLD AGE HOME AND DISEASE PREDICTION USING IoT AND MACHINE LEARNING

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Abstract

In recent years IoT devices has been very beneficial for the healthcare industry, it provides the continuous health monitoring updates which helps to improve the lifestyle of human. This IoT device generates huge amount of data which is stored on cloud, so cloud-based scenario plays an important role in this rapid changing world. Experts in this field of healthcare sought to robotize the way to identify and treat the diseases that can potentially exploit IT innovation. Today's enhanced possibilities of the emerging networked environments hold a promise to reduce healthcare costs, workload and occupancy of healthcare facilities by using wireless technologies in providing health services outside the hospital environment. This paper represents a literature review of smart old age homes for people, where a system will work to monitor the health of an individual and generate a report on weekly basis which help to diagnose them before it is too late. The early diagnosis is always better and this can be achieved by using IoT devices, cloud service and machine learning.

Keywords- Smart Old-Age Home, Sensor, Machine Learning, Smart System, Early Detection, Cloud Computing, IoT.

I. INTRODUCTION

Most importantly the purpose of this work is to provide smart home facility so that the elderly one does will get the great experience in their day to day life. The Smart Old-Age home is designed to monitor the well being of elderly people. The well being can also be maintained from natural environment, because it helps to reduce stress, helps to attach emotional well being and also recover the people naturally. That's why it is important to maintain contact with nature. The priority of the elderly peoples experience in a residence should take into account for their fundamental needs and the resulting benefits. The purpose of this study is to suggest the smart home technologies and provide a framework which contains smart home services which can diagnose the elderly on daily basis. Now a day's 18+ adults are having at least one chronic disease, which may cause serious when they will be in their elderly stage or after 60'S.

These chronic diseases are the beginning of serious disease which will happen in elderly age, and in this elderly age it is difficult to cure it from the roots. We can only treat it at the extent where it can be controlled, just like adults take the pain killer for some chronic disease just for relief, without thinking to remove it from the root. That's why the elderly may require the frequent or immediate treatment otherwise it may result in fatal consequences. And to avoid such emergency situation there should be a continuous fashion physiological monitoring system which helps to monitor the health related parameter.

Most emergency elderly cases seek in patient care, which is very expensive due to the long stay in hospital and have to face the financial burden too, Since we are concerning specially for old age home this financial burden have to be faced by the old age home committee. On the other hand, Remote health monitoring is a smart home platform, which allows people to stay at home, to remain in their own environment and comfortable zone rather than to have an expensive limited hospital space and nurses. Sometimes the hospitals environment is also responsible for the patients weakness, because the morale of patient goes so low in that single room of hospital that it may cause more serious health, which cause due to the lost of their own dependency. Hence it is a generous need of people now, to live in a smart home, which provides the facilities for the well being of an elderly.

The smart homes are outfitted with prudent and non-invasive environmental and physiological sensors and actuators that can help to facilitate remote monitoring of the home environment such as temperature, humidity, smoke in the home, as well as some important physiological signs such as heart rate, body temperature, blood pressure and blood oxygen level and some activities of person. This healthcare facility also ensures to remotely communicate with the caregivers, and allows keeping and maintaining the record of the occupants and give advice after tracking complete physiological condition of the occupant.

II. LITERATURE REVIEW

The use of IoT-based devices is changing people's lifestyles, especially in activities which are related to healthcare. In this significance, IoT-based devices can monitor, analyze, diagnose, and contribute to the generation of medical pleading for various health conditions, such as overweight and obesity. For this reason, this topic has become the main focus in recent research. In this work, we have presented a review of the state of the art of research involving the IoT in healthcare, particularly withrespect to overweight, obesity, and chronic degenerative diseases.

Vasquez etal.[1] proposed "mhealth", a health platform that contributes to improving child nutrition by monitoring their data and sends notifications and provide messages based on the choice of food which is very informative.

InVilallonga et al.[2] presented a study conducted on a group of obese patients having undergone surgery, who found it very motivating to observe, easily and quickly, a consistent graphic representation of their activities. Mun-Lee and Ouyang [3] presented a study that strive to identify correlations between the risks of developing certain diseases and used healthcare devices in reference with IoT. Zaragozá et al.[4] presented a platform which has been provided to use intercommunicated sensors to monitor the activities of children with their obesity problems.

Mun-Lee and Ouyang [5] proposed a collaboration protocol to send risk notifications to smart devices used in the IoT, along with a new service application algorithm that was used in devices linked with patients with blood pressure problems, obesity, and diabetes. Hiremath et al. proposed a proposal for the conceptualization of wearable IoT (WIoT) in terms of applications, functions, and design. In addition, they proposed a system for WIoT that recommends new directions regarding clinical and operative procedures.

Kim et al. [6] presented the iN Touch mobile application to monitor the daily activities of underprivileged young people with overweight and obesity who participated in a health apprenticeship program.

Alloghani et al. [7] presented a mobile application to increase children's and parents' awareness of the consequences of being overweight and obese, while providing information on how to sustain a healthy and balanced diet. Wibisono and Astawa [8] proposed a web page and a mobile application for the treatment of weight reduction through machine-to-machine (M2M) information exchange or communication, in which a specific proportion of weights was used to achieve a healthy diet. Dobbins et al. [9] proposed a method to obtain physiological data from devices linked to triaxial accelerometers and a heart rate monitor, in order to detect physical activity. Likewise, they evaluated the performance of the classifiers in relation to the physical activities of the patients. Additionally, Shin et al.[10] defined a new concept of IoT-learning, with which a health application was developed using a combination of the IoT and architecture supported by the IoT. Likewise, they proposed a patient-focused treatment using IoT-learning to maintain weight.

Jeong et al.[11] proposed the development of IoT HEALTHCARE, describing its architecture as a smart alternative for healthcare. IoT HEALTHCARE used sensors connected to a network to collect medical variables; later, the data were analyzed through algorithms validated by health personnel to generate recommendations.

By contrast, Gupta et al. [12] proposed architecture supported by embedded sensors in the equipment, avoiding the use of wearable sensors or smartphone sensors, with the purpose of safeguarding basic health-related medical information.

III. PROBLEM ANALYSIS

As per the current scenario, if the patient is having any health-related problems then according to symptoms, he/she must visit the hospital or consult the doctor to diagnose the disease. But, our main objective is to reduce such efforts taken by patients only to diagnose the disease. Many patients are losing their life only because of the late diagnosis of their disease. So our main aim is to reduce such deaths.

The existing system predicts the chronic diseases which are for a particular region and for the particular community. Only particular diseases are predicted by this system. In this System, Big Data & CNN Algorithm is used for Disease risk prediction. For S type data, the system is using

Machine Learning algorithm i.e. K-nearest Neighbors, Decision Tree, Naïve Bayesian. The accuracy of the existing System is up to 94.8%.

Smart-home technology and related services can reinforce a person's experiential nature, promoting sustainable living among the elderly. It is crucial in the housing industry that support "Aging in Place", contributing to the contact, control, and simulation of nature at home as well as the creation of a high-quality living space instead of mechanical achievement. Further, biophilic experience, the strengthening of inherent human propensity to nature for optimal health and well-being, supports the elderly's physical, mental, and sociological health. However, despite the continuing emphasis on the benefits of residential nature experiences for the elderly, the application of smart-home technology and services is insufficient.

IV. PROPOSED WORK

Smart-home services consist of sensors, controllers, actuators, displays, and other smart devices and systems as a network, enabling the localization and remote control of domestic environments as well as automation. The home network gathers and stores data transmitted from the input device through the home gateway or platform and converts it into a single protocol to deliver it to the output device. Smart-home services for the elderly aim to strengthen physical, mental, and social health management of the elderly and can be categorized into health monitoring (HM), environment monitoring (EM), risk management (RM), communication management (CM), and sensor management (SM); details are shown in Figure 1.

Smart-home technology is being used to support the various needs of the elderly, and the fundamental goal of all technologies and services is to improve the QoL of humans. From this perspective, although smart-home services maximize the convenience and efficiency of housing for the elderly and families, it is often seen as a "mechanical utopia" rather than a high-quality living space. Up to now, smart homes for the elderly have focused on checking their health status in real time, responding to crisis situations as quickly as possible, and communicating more easily with medical professionals or family members. Importantly, despite the continuing emphasis on experiences with nature in the residential environment of the elderly, discussions about applying it to smart technology or turning it into a service are insufficient. This stems from the perception that nature and smart-home technology are contradictory concepts; another reason is that smart-home-related research usually focuses on the modernization of existing smart-home service systems.

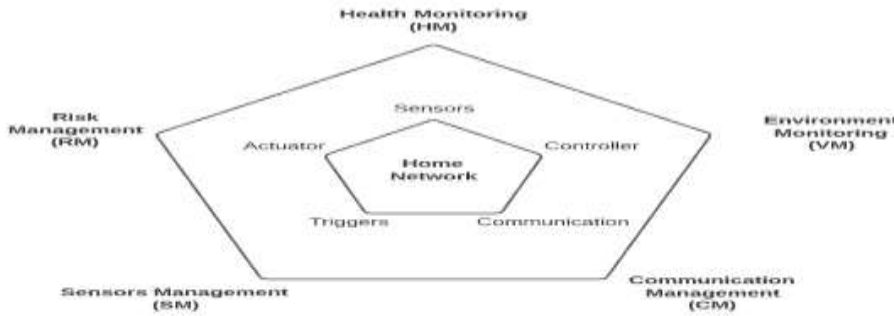

Figure 1: Service Components and contents

However, the development of smart-home technology and its devices to date can be effectively used in contacting, controlling, and directing nature within the home environment, and the concept of biophilia based on the relationship between humans and nature could lead to a new trend in the smart-home industry; thus, biophilia must be considered. Therefore, the smart-home service for the elderly should focus on supporting a more multi-sensory nature experience and immersion in the experience by easing the limitations of the physical, regional, and geographical conditions, and should provide a high-quality residential environment by connecting nature and technology.

V. SYSTEM DESIGN

➢ Block Diagram and System Flow

Most of the chronic diseases are predicted by our system. It accepts the structured type of data as input to the machine learning model. This system is used by end-users i.e. patients/any user. In this system, the user will enter all the symptoms from which he or she is suffering. These symptoms will be given to the machine learning model to predict the disease. Algorithms which are applied gives the best accuracy. Then System will predict disease on the basis of symptoms. This system uses Machine Learning Technology. Naïve Bayes algorithm is used for predicting the disease by using symptoms, for classification KNN algorithm is used, Logistic regression is used for extracting features which are having most impact value, the Decision tree is used to divide the big dataset into smaller parts. The final output of this system will be the disease predicted by the model.

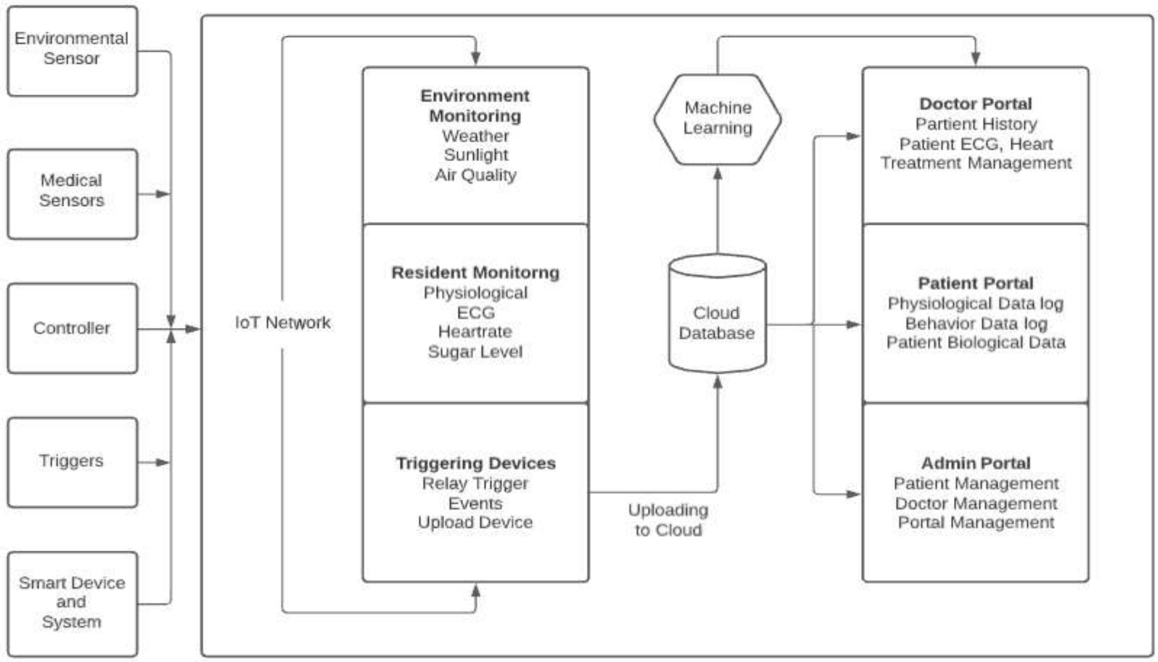

Figure 2: Work flow in smart old age home

Our proposed smart-home service framework uses sensors and devices that support the biophilic experience and IoT-based smart devices as service resources, while devices that can monitor and control status information in the house are used through a home gateway, and IoT-based devices are configured to be controlled through the IoT cloud. The smart-home platform manages device information transmitted through the smart gateway and each IoT cloud and converts and integrates protocols of all devices into resources for smooth service provision and collaboration.The home gateway and IoT cloud mutually communicate, and all devices delivered to the smart-homeplatform through the home gateway are converted to follow the same protocol and classified into environment/resident/device resources according to their functions. Environment and residents are resources for environmental monitoring, environmental control, and resident information recognition inside and outside the house, and the devices are comprised of the resources used for the interaction with the IoT cloud to provide services that are input or output to IoT-based smart devices. The resource list is delivered to set resource collaboration (SRC), thereby making integrated control and additional collaboration possible by users or administrators. That is, once the SRC is completed, the data resource of the input device is defined accordingly, and all repeated processes are stored in the database of the smart-home platform. This study organized the input and output devices that support the biophilic experience service according to the service framework, Moreover, we proposed the interaction characteristics of smart-home devices from the perspective of residents and space, in consideration of efficient service provision and physical application in the house. From the perspective of residents, the interaction method was analyzed based on whether direct interactions such as physical contact and physical manipulation occur, and the spatial viewpoint is related to the shape of the device and the installation method in the space, so that the user can visually recognize the device. That is, the interaction is classified based on whether the device is attached to the existing environment, invisibly embedded into the space, or integrated in the form of a home appliance to replace the existing one (i.e., M, SE, or EE). The interaction characteristics of smart-home service devices from the perspectives of residents and spatial considerations are referred to as contact-SE, contact-EE, noncontact-M, noncontact-SE, and noncontact-EE, excluding contact-M. Contact-SE are devices that require direct interaction by residents and are embedded in existing facilities or spatial structures, including smart kitchens and toilets for waste collection and disposal, smart windows with built-in touch screens, and wall displays. Contact-EE are smart devices or autonomous objects that require the physical manipulation of residents, including smart phones that provide remote control applications, natural language recognition, and social robots that can communicate. Therefore, it is important to provide smart-home services from an integrated perspective. The way in which residents interact with smart-home devices should be adjusted according to the residents physical and mental characteristics and should support cost savings and space efficiency through intelligent and smart devices that provide a variety of functions in place. The service-assisted devices and interaction characteristics proposed in this study distinguish active and passive use of residents by input and output devices and contribute to the search for physical methods of applying smart-home devices in the residential space.

➢ Algorithm and Methods:

KNN:

K Nearest Neighbor (KNN) could be terribly easy, simple to grasp, versatile and one amongst the uppermost machine learning algorithms. In the Healthcare System, the user will predict the disease. In this system, the user can predict whether the disease will detect or not. In the proposed system, classifying disease in various classes that shows which disease will happen on the basis of symptoms. KNN rule used for each classification and regression issue. KNN algorithm is based on feature similarity approach. It is the best choice for addressing some of the classification related tasks. K-nearest neighbor classifier algorithm is to predict the target label of a new instance by defining the nearest neighbor class. The closest class will be identified using distance measures like Euclidean distance. If K = 1, then the case is just assigned to the category of its nearest neighbor.

The value of ‘k’ has to be specified by the user and the best choice depends on the data. The larger value of ‘k’ reduces the noise on the classification. If the new feature i.e in our case symptom has to classify, then the distance is calculated and then the class of feature is selected which is nearest to the newer instance. In the instance of categorical variables, the Hamming distance must be used. It conjointly brings up the difficulty of standardization of the numerical variables between zero and one once there's a combination of numerical and categorical variables within the dataset

NAIVE BAISE:

Naive Bayes is an easy however amazingly powerful rule for prognosticative modeling. The independence assumption that allows decomposing joint likelihood into a product of marginal likelihoods is called as 'naive'. This simplified Bayesian classifier is called as naive Bayes. The Naive Bayes classifier assumes the presence of a particular feature in a class is unrelated to the presence of any other feature. It is very easy to build and useful for large datasets. Naive Bayes is a supervised learning model.

LOGISTIC REGRESSION:

Logistic regression could be a supervised learning classification algorithm accustomed to predict the chance of a target variable that is Disease. The nature of the target or variable is divided, which means there would be solely 2 potential categories. In easy words, the variable is binary in nature having information coded as either 1 (stands for success /yes)or 0 (stands for failure / no). Mathematically, a logistic regression model predicts(y=1) as a function of x. Logistic regression can be expressed as: $\log(p(X)/(1-p(X)))=\beta_0+\beta_1 X$ where the left-hand side is called the logistic or log-odds functionand $p(x)/(1-p(x))$is calledodds.The odds signify the ratio of the probability of success to the probability of failure. Therefore, in logistic regression, a linear combination of inputs is mapped to the log(odds) - the output is adequate to 1.

DECISION TREE:

A decision tree is a structure that can be used to divide up a large collection of records into successfully smaller sets of records by applying a sequence of simple decision tree. With each successive division, the members of the resulting sets become more and more similar to each other. A decision tree model consists of a set of rules for dividing a large heterogeneous population into smaller, more homogeneous (mutually exclusive) groups with respect to a particular target.

- The target variable is usually categorical and the decision tree is used either to:
- Calculate the probability that a given record belong to each of the category and,

To classify the record by assigning it to the most likely class (or category).

In this disease prediction system, decision tree divides the symptoms as per its category and reduces the dataset difficulty.

VI. IMPLEMENTATION

Dataset used in this system is in a structured format. The dataset which is used contains the disease name with its all symptoms. As our system is based on supervised learning machine algorithms, the dataset is having the label with 0 or 1. Then we divide the dataset into a Training dataset and Testing dataset. The model is trained by a training dataset. All algorithms were applied to this training dataset and then the machine learning model is trained. Then the testing dataset was provided to the trained model to test the accuracy of the model.

The hospital data will be in the form of structural format. The dataset used in this project is real-life data. The structural data contains symptoms of patients. Any dataset is converted into either

0 or 1. Zero value represents feature/symptom impacts on disease and value one represents that it does not impact on disease.

Accuracy-:

$$\frac{TruePositive+TrueNegative}{TruePositive+TrueNegative+FalsePositive+FalseNegative}$$

$$\text{Precision} = \frac{TruePositive}{TruePositive+FalsePositive}$$

$$\text{Recall} = \frac{TruePositive}{TruePositive+FalseNegative}$$

$$\text{F1-Measure} = \frac{2\times precision\times recall}{precision+recall}$$

Recall and Precision formula

To calculate performance evaluation in the experiment, first, we denote TP, TN, Fp and FNias true positive(the number of results correctly predicted as required), true negative (the number of results not required), false positive (the number of results incorrectly predicted as required), false negative(the number of results incorrectly predicted as not required)respectively. We can obtain four measurements: recall, precision, accuracy, and F1 measures as follows:

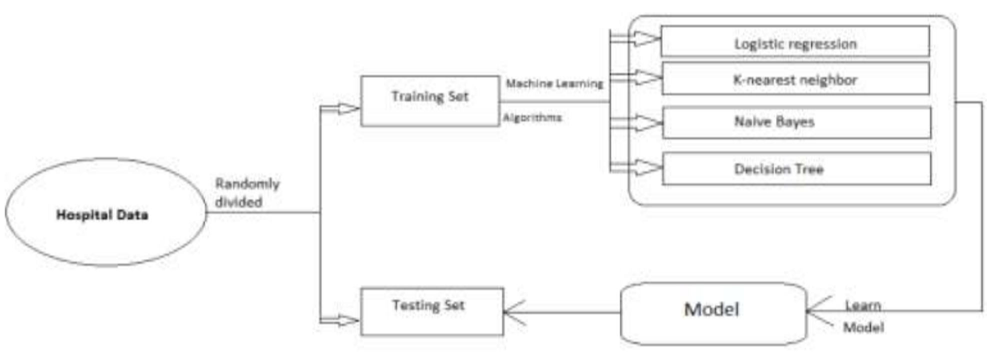

Figure 3: Dataset Architecture

VII. RESULT

Figure 5 shows the system hardware implementation where microcontroller, sensor, NodeMCU module, relay and load are interconnected to each other.Once the data get collected from these devices, it store in Thinkspeak's cloud which then retrieved by the machine learning model for the prediction of the particular disease and it will shows on treatment record refers figure 9.

The user has to first sign-up with their valid credentials and then they can login and in their login page they can see the all medical history and the automated system management via admin dashboard, it gives manage patient option figure 8 to doctor for tracking down all the dedicated data and the previous history of treatment for that particular user, as the KNN algorithm determines the accurate chronic diseases.

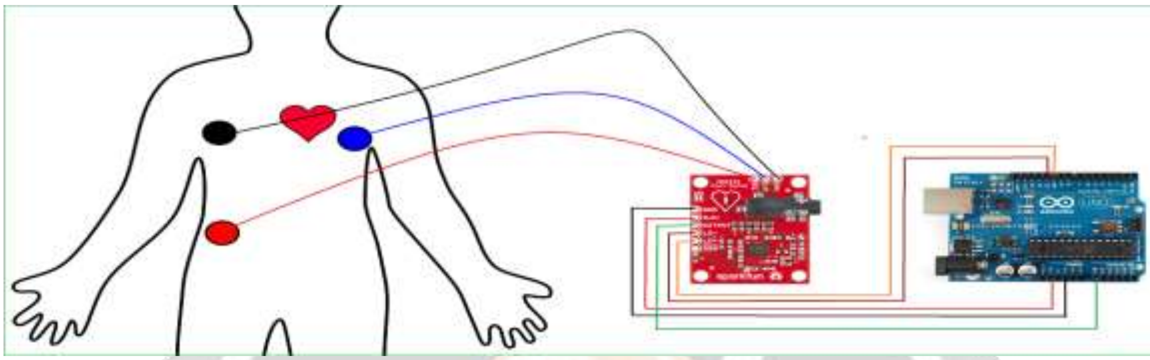

Figure 4: Sensor Placement on body

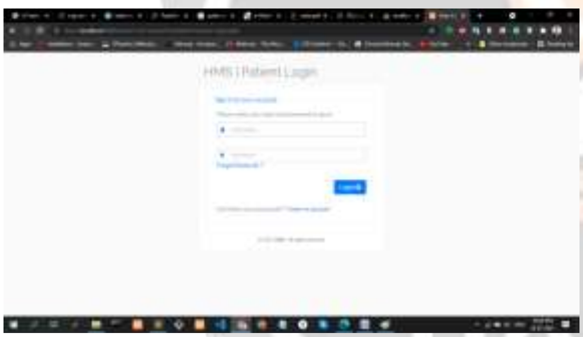

Figure 5: Patient Login

Figure 7: Medical History

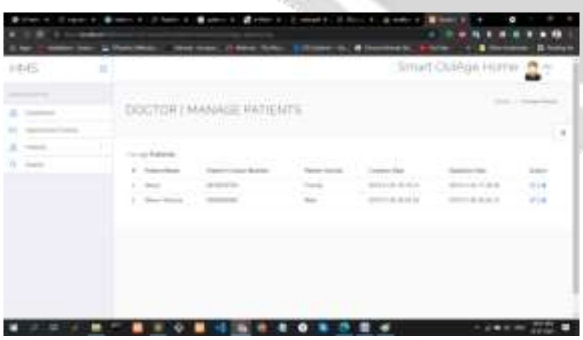

Figure 6: Manage Patient

Figure 8: Treatment Record

Figure 5 - This is the Patient Login window which been used to log in the user as a patient or incase if the patient is not registered with the HMS then he/she can create their new account using ‘Create an account’ link. Figure 6 - Patients list gives the brief about the system registration to the admin as it maintain all users list with the action tab to the particular patient with that we can easily manage all the terms and the Patient + Doctors. Figure 7- This deals with the patient medical history by what the patient previously treated so their complete treatment record by particular so no need to maintain paper records. Figure 8 - This deals with history details it gives all the history of particular treatment with ECG maintain value or heart rate value and glucose level in blood.

VIII. CONCLUSION

In our research the main aim of this disease prediction system is to predict the disease on the basis of the symptoms. This system takes the symptoms of the user from which he or she suffers, as input and generates final output as a prediction of disease. Average prediction accuracy probability of 100% is obtained. Disease Predictor was successfully implemented using the grails framework. This system gives a user-friendly environment and easy to use. As the system is based on the web application, the user can use this system from anywhere and at any time. In conclusion, for disease risk modeling, the accuracy of risk prediction depends on the diversity feature of the hospital data.

This contribution broadens the understanding of how to experience nature from the perspective of a sustainable residential environment. Moreover, it has value in managing positive experiences and maintaining a high QoL in the elderly in smart homes. In particular, the biophilic experience-based smart-home services content proposed in this study informs the expansion of the aged-friendly smart-home industry and contributes to the development of smart-home services along with new service trends.

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