ESTIMATING LENGTH OF STAY AND AFTERCARE IN THE RECOVERY OF PATIENTS WITH STROKE

[1]Venkat Kumar M, [2]Nandha Kumar K, Hemanth Kumar P[3], Suresh C[4]

[1,2,3]Student, [4]Assistant Professor
Department of Information Technology
Gojan School of Business and Technology, Redhill's, Chennai-600 052.

Abstract: **Hospital length of stay (LOS) of patients is an important** factor **for planning and managing the resource utilization of a hospital. There has been considerable interest in controlling hospital cost and increasing service efficiency, particularly in stroke and cardiac units where the resources are severely limited. This study introduces an approach for early prediction of LOS of stroke patients arriving at the Stroke Unit of King Fahd Bin Abdul-Aziz Hospital, Saudi Arabia. The approach involves a feature selection step based on information gain followed by a prediction model development step using different machine learning algorithms. Prediction results were compared in order to identify the best performing algorithm. Many experiments were performed with different settings. This paper reports the performance results of the two most accurate models. The Bayesian network model with accuracy of 81.28% outperformed C4.5 decision tree model (accuracy 77.1%).**

Index Terms: Length of stay, Stroke patients, Bayesian network.

II.   INTRODUCTION:

Stroke, also known as cerebrovascular accident (CVA) is a sudden and devastating illness that is characterized by the rapid loss of brain function due to a disruption of blood supply to the brain. This disruption is caused by either ischemia (lack of blood flow) which counts for more than 80% of all strokes [1], blockage of blood flow, or hemorrhage (loss of blood) [2]. Based on previous studies, Stroke is the second cause of death worldwide after cardiac disease, cancer, and chronic lower respiratory disease [3]. The length of stay (LOS) of a stroke patient varies depending on various factors describing the patient's medical condition [4]. LOS is defined as the number of days a patient is required to stay in a hospital or any healthcare facility for treatment [5], [6]. LOS is an important factor for planning and managing the resource utilization of a hospital [7]. There has been considerable interest in controlling hospital cost and increasing service efficiency, particularly in stroke and cardiac units where the resources are severely limited; thus hospitals try to reduce LOS as much as possible [8]. Moreover, reducing the LOS purportedly yields large cost savings [7], [9]. A model to predict the length of stay (LOS) of stroke patients at an early stage of patient management can effectively help in managing hospital resources and increase efficiency of patient care. Such a prediction model will enable early interventions to reduce complications and shorten patient's LOS and ensure a more efficient use of hospital facilities. Most previous research uses statistical techniques to identify factors determining the LOS and the prediction of LOS is made using regression models [4], [6], [9], [10]. Recently, with the availability of large amounts of patients' data, data mining approaches to predict LOS are becoming increasingly promising [5], [11]–[16]. In healthcare, data mining has been used for diagnosis and prognosis of illness and for predicting the outcome of medical procedures [16]–[23]. Data mining techniques such as classification, artificial neural networks, clustering etc. are used to discover data patterns and relationships among a large set of factors and to construct reliable prediction models based on the given input data. To predict LOS of patients, Wrenn et al. [15] proposed an artificial neural network-based prediction model for an Emergency Department. Rowan et al. [13] proposed to predict LOS of cardiac patients using artificial neural networks based on preoperative and initial postoperative factors. Azari et al. [24] proposed a multi-tiered data mining approach for predicting LOS. They used clustering technique to create a training dataset to train several classification algorithms for prediction of LOS. Classification algorithms were also used by Hatches et al. [5], and Jiang et al. [14] for predicting LOS. They have demonstrated multiple classification algorithms (decision tree, support vector machines, logistic regression) with varied level of accuracy. Most of the previous works emphasized on the use of novel or hybrid classification algorithms or complex ensemble models [12], [14]. However, the performance of any prediction model depends on the number and type of its inputs variables as well [25]–[26]. Thus, the selection of appropriate input variables or features is critical to the performance of any prediction model. In this work, we proposed to solve the LOS prediction problem using a novel approach combining a feature selection step for optimum mix of input features with a prediction model development step using classification algorithms. Our aim is to provide an early LOS estimation for new patients arriving at a stroke unit.

III.   EXISTING SYSTEM:

We categorized data values and derived new fields from existing data in the following features: ejection fraction, diastolic blood pressure, systolic blood pressure, smoking, triglyceride, low-density lipoprotein, high-density lipoprotein, hemoglobin, serum cholesterol, and fasting blood sugar. These features were changed to categorical attributes for analysis and to obtain bad results. Predicting the length of stay (LOS) of patients in a hospital is important in providing them with better services and higher satisfaction, as well as helping the hospital management plan and managing hospital resources as meticulously as possible. We propose applying data mining techniques to extract useful knowledge and draw an accurate model to predict the LOS of heart patients. Research in recent years has revealed factors that are important predictors of physical and functional rehabilitation:

demographic variables, visual and perceptual impairments, and psychological and cognitive factors. However, there is a remaining uncertainty about prediction of outcome and a need to clinically apply research findings. This study was designed to identify the relative importance of medical, functional, demographic, and cognitive factors in predicting length of stay in rehabilitation, functional outcome, and recommendations for post discharge continuation of services.

IV. PROPOSED SYSTEM:

In this work, we proposed to solve the LOS prediction problem using a novel approach combining a feature selection step for optimum mix of input features with a prediction model development step using classification algorithms. Our aim is to provide

V. DISADVANTAGES:

O   They proposed using the HR model to predict the mean LOS of stroke patients.
O   The largest advantage of a registry is the ability to prospectively add patients, while allowing investigators to go back and collect information retrospectively if needed.
O   These features were changed to categorical attributes for analysis and to obtain bad results.

VI. ARCHITECTURE DIAGRAM:
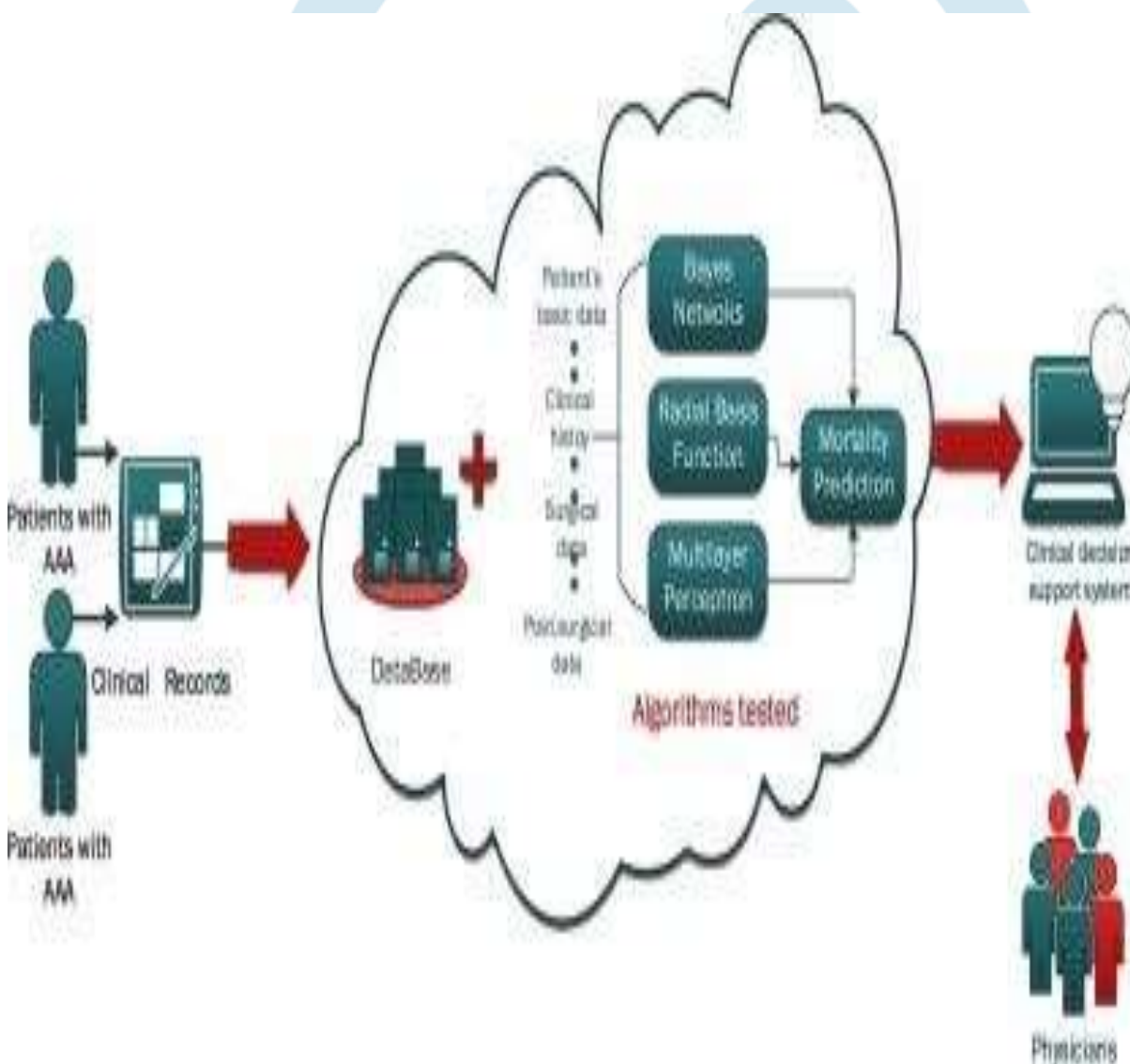
VII. MODULE EXPLANATION:

The login module is the very first and the most common module in all applications. In the suggested system only, registered users will be allowed to login the system the unauthorized users will be unable to login. Registered users with their username and password only being correct will moved on to the next page. Or else they will be unable to login. Logout means to end access to a computer

system or a website. Logging out informs the computer or website that the current user wishes to end the login session. Log out is also known as log off, sign off or sign out. The login module is the very first and the most common module in all applications. In the suggested system only, registered users will be allowed to login the system the unauthorized users will be unable to login. Registered users with their username and password only being correct will moved on to the next page. Or else they will be unable to login. Bed management is the allocation and provision of beds, especially in a hospital where beds in specialist wards are a scarce resource. The "bed" in this context represents not simply a place for the patient to sleep, but the services that go with being cared for by the medical facility: admission processing, physician time, nursing care, necessary diagnostic work, appropriate treatment, and so forth. Logout means to end access to a computer system or a website. Logging out informs the computer or website that the current user wishes to end the login session. Log out is also known as log off, sign off.

VIII. CONCLUSION AND FUTURE ENHANCEMENT:

This study introduces an approach for early prediction of LOS of stroke patients arriving at a stroke unit. The approach involves a feature selection step based on information gain and a prediction model development step using J48 decision tree or Bayesian network. Prediction results were compared between the two models. The performance of the Bayesian network-based model was better (accuracy 81.28%) as opposed to the performance of the J48 based prediction model (accuracy 77.1%). A partial representation of the J48 based model and the Bayesian network-based model are exhibited Nevertheless, the performance of the proposed prediction model is quite promising. In future studies, the proposed approach will be tested on larger datasets. Another important area for future research is to extend the proposed approach predict other attributes such as the Stroke Level of the patients.

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