

CHAPTER 47

Predicting the Hospitalized Patients Result from the Electronic Health Report

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ABSTRACT

Generally, two types of patients are admitted to hospitals. In them the outpatient department will be operational to monitor the patients coming in daily and their details will be constantly uploaded in the outpatient data and stored in the database. But inpatient data are not updated daily. The inpatients stay in that hospital for some time and receive treatment for their illness. Thus they are treated for various ailments while they are there. Thus the way outpatients are treated does not apply to inpatients. In this paper an algorithm based on a machine learning process for dealing with inpatients is proposed. Then the depending on the nature of the disease, the duration of treatment given to it, the approximate amount they show and the advice given to them, their stay in the hospital is calculated and its data is recorded in the database. Thus the further enhancing of the patient care process. The accuracy of this method is 99.18% so its use is high.

Keywords: *Inpatient, outpatient, machine learning, patient data, electronic health reports, treatment*

INTRODUCTION

In general, the hospitals dedicated to health services are under constant pressure of high costs, while at the same time being subject to ever-increasing demands on patients, social services, government agencies and the community as a whole. Continued advances in technology and science force both the acquisition of new equipment and the continued education and training of medical and paramedical personnel [1]. The machine learning models are changing the work ethic on several factories. Most of it offered by an Artificial Intelligence and Machine learning collect data sequence from everypacket that cannot collect

information from multiple sources. [2]. With its expansion into business organizations, technological advancement has driven artificial intelligence and Machine learning touches a more restrained and closes fraternity in the health and medical sciences. It promises to sustain key policies and bring significant growth. It focuses more on increasing quality maintenance and reducing the cost of procedures. Machine learning offers benefits not only for physical time but also for providing teleconsulting and care to those in geographical situations. The technology-enabled monitoring system provides a continuous stream of patient data over the Internet, regardless of demographics, reflecting how many events have occurred in the past [3-7]. Machine learning models have proven to be useful for people in need of care where they are not physically accessible. As the use of technology to collect and read data has evolved and routine outpatient department to function flawlessly [8].

When a person has a sudden heart attack through artificial intelligence, it will be known to the hospital where he is being treated in a few seconds. At the same time his family will be informed. Rescue teams can automatically come to his place and pick up the patient and take him to the hospital [9]. And doctors can control a patient's heart rate just as they would in a hospital. All of this can be demonstrated by artificial intelligence without the patient being stimulated individually for a few seconds after the patient has had a heart attack [10].

The machine learning analysis is a practice of data analysis that mechanizes the model structure. A true machine learning system is one in which the learning machine is constantly learning to understand its functions correctly and the intelligence is new [11-13]. The data is fed into the learning machine with each active and passive feed, and then the task is automated without the need for continuous human or manual intervention. Machine learning has allowed computers to detect hidden intelligence and use retrieval mechanisms to retrieve data provided to them without having to plan where to look [14]. Machine learning can unleash new strategies and productivity in a variety of settings, including information technology, healthcare, logistics, energy and education. Self-learning algae can achieve unprecedented performance in business systems, and on a personal level, smart gadgets can really guide us through everything and make our lives easier [15].

LITERATURE REVIEW

Elhoseny M et al. [3] calculated the number of patients with in-patient or out patients in the United States-based population. That means that a total of more than 7 lakh people are reported to be living everyday life with differen types of in-patient or out patients and they estimate that 80% of them are benign malignant in-patient and the other 20% are malignant out patients.

El-Dahshan et al. [4] released some data based on current opinion polls. According to the latest estimates, 80,000 people are affected by in-patient diseases. 55,000 of them are classified as belonging to Types 1 and 2. A further 25,000 people are reported to be affected by type 3- and type-4 out patients.

Kong Y et al. [5] further simplified the Computation of in-patient or out patients. Evolving technologies are increasingly making it easier to calculate and classify in-patient or out patients. And the rise of Machine learning-based achievements has created a major industrial revolution in this modern age and has made the series of health structures even more special.

Rao CH et al. [6] Computed tomography was performed on different types of in-patient or out patients. They examined and evaluated their series of health conditions. The status of the patients and the risks associated with its condition can be calculated by these procedures.

Islam A et al. [7] Designed a model based on simple processes that classify brain in-patient or out patients. The nature and severity of the disease were diagnosed and analyzed based on the data in its proposed manner. Its improved procedure and Computations accurately calculated the classification of in-patient or out patients.

A. A. Alshehri et al [8] proposed some improved methods for differentiating and analyzing the types of in-patient or out patients in the gallbladder. It was designed based on the process of calculating the structure of in-patient or out patients from MRI patients using specific individualization processes. To confirm the patient details accuracy of this design, they approved more than 300 MRI scans of 14 patients with different in-patient entries. This process showed the patients alone and the functions of the brain alone.

PROPOSED METHOD

The proposed Smart patient predicting algorithm (SPPA)model shown in the following fig.(1) and the algorithm used in the SPPA model has been elaborated in Algorithm 1. In machine learning, you have set up some training data for PC training. It uses data to create a model, and uses it to make predictions as it receives new input.If the prediction appears to be incorrect, the PC restarts the process once it has made the correct prediction.The computer learns to make a prediction every time because it is necessary to watch. This is just an easy example. Machine learning methods are very complex and require many steps. Completely different machine learning tools help you discover the depth of data science domains, experiment with them, and innovate fully functional AI / ML options. Completely different tools are designed for different needs. Therefore, the choice of machine learning tools will largely depend on the task at hand, the expected end result and generally your professional level.There are three distinctions in machine learning - supervised learning, non-supervised learning and reinforcement learning.

Algorithm 1 : Smart patient predicting algorithm (SPPA)

1. Initialize input details of the patient
2. Store the patient details for computation
3. *if* (Patient details = database)
4. Thenmove to disease analyzed
5. Update the details in patient electronic records
6. *if*(Patient details = in-patient)
7. Then move to patient disease validation module
8. *if*(data validation > 90%)
9. Then declare type 4 in-patient

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10. *elseif*(data validation \leq 89% and $>$ 70%)
 11. Then declare type 3 in-patient
 12. *elseif*(data validation \leq 69% and $>$ 50%)
 13. Then declare type 2 in-patient
 14. *else*declare type 1 in-patient
 15. *else*declare the patient as “Out-patient”
 16. *else*go to step 2
 17. end
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1. Supervised learning- Computers are capable of predicting future outcomes based on past data. This type of learning requires a training model to accomplish any task.

2. Unsupervised Learning - Hidden patterns are determined by exploring from the input data provided without the need for any training.

3. Reinforcement learning - This type of learning method follows a trial and error method in which the most rewarding method is determined.

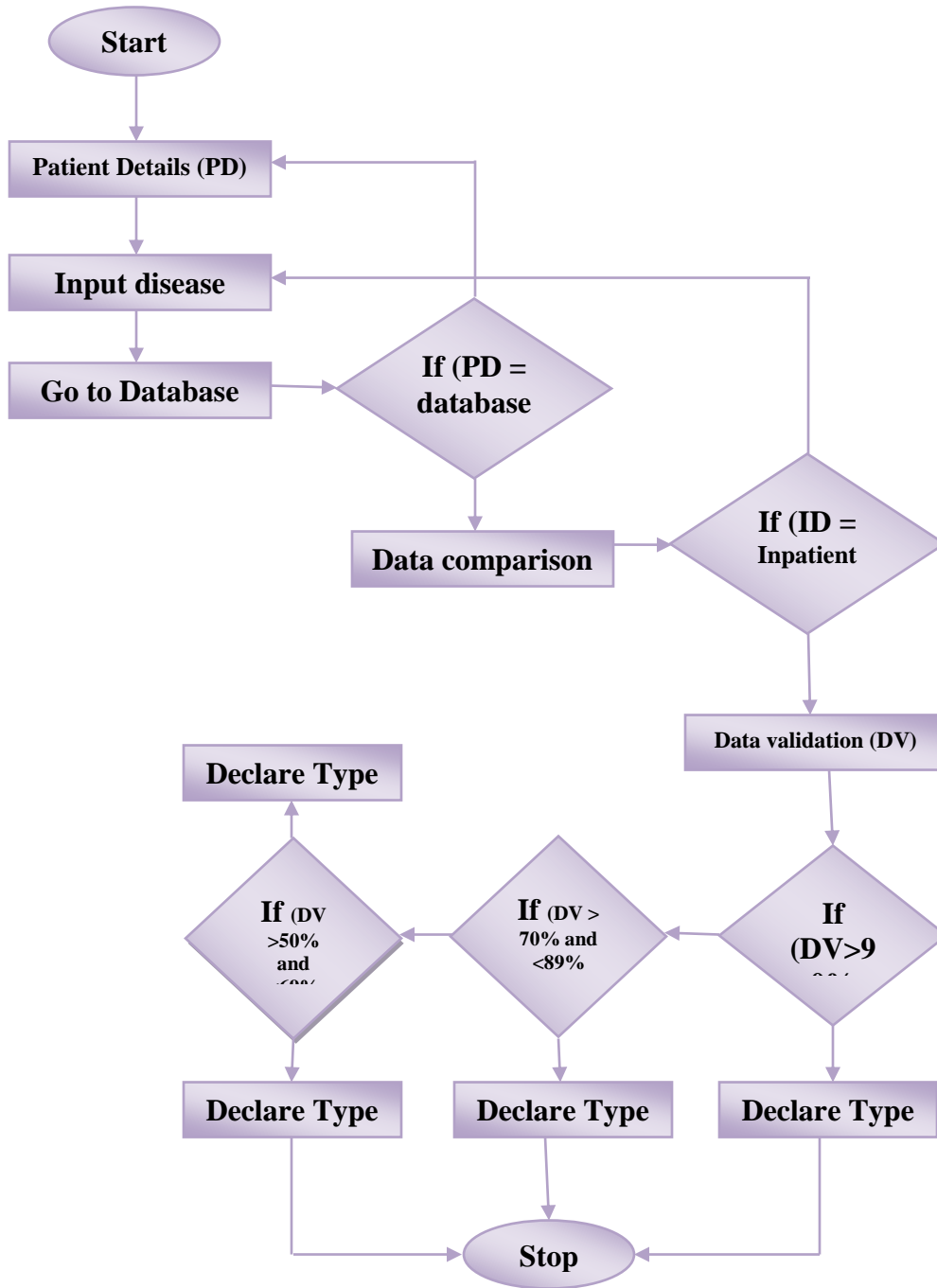


Fig 1: Proposed system design

Artificial intelligence often refers to a field that involves simulating human intelligence in machines using normative programs or data. Although artificial intelligence refers to simulating human intelligence in machines, the good part is that there are many ways to achieve it. As mentioned earlier, one way is to design hard-coded, rule-based programs using unique mathematical tools, statistics, and other algorithmic

approaches. However, another approach is to improve data availability and use different mathematical fields (linear algebra, probability, statistics, etc.) to design mechanisms that help machines understand data formats. This field of designing and implementing algorithms that help machines identify patterns within data is called machine learning.

Again, there are different approaches to using machine learning depending on the properties of the data. Deep learning is a subfield of machine learning that involves the use of deep neural networks. It should be noted that "neural networks" with a single layer can only learn linear patterns within a data. When data has non-linear forms, more than one hidden layer is required, so such networks are called deep neural networks, which are deep learning for it. Extensive mathematical evidence and theory are available online, which explains why multiple hidden layers are able to detect nonlinear patterns in data.

RESULTS AND DISCUSSIONS

The proposed Smart patient predicting algorithm (SPPA) was compared with the existing A hybrid fuzzy optimization algorithm (HFOA), Multi-fractal texture estimation (MTE), Segmentation based Chi-Square Fuzzy C-Mean Clustering (SBCC), hybrid feature extraction method (HFEM)

There are the 5 parameters are evaluate the water quality. That is the patient details accuracy, patient details precision, patient details recall, Patient details F1-Score and computation time. Before understand the quality rate of the parameters, will know about the following,

Positive-T (TP)—It's the perfect predicted correct or above thecalibration level.

Negative-T (TN)—It's the negative prediction values below the calibration level.

Positives-F (FP) – When the exact values are in calibration level and the predicted Records are in same level

Negative-F (FN) – When the exact values are in calibration level butthe predicted Records are in different level

4.1. Computation of patient details accuracy:

The Patient details accuracy is the parameter which describes the ratio between perfectly predicted patient details input patients from the given Records to the total number of collected patientRecords. When the rate of patient details accuracy is high then the given output patient sample getting high quality rate.

$$\text{Accuracy Measurement} = \frac{TP+TN}{\text{All collected samples}} \quad (1)$$

The below table 1demonstrates the various measurement comparison of the patient details accuracy values between the existing HFOA, MTE, SBCC, HFEM and proposed SPPA

Table 1: Measurement of Patient details accuracy

| No.ofRecords | Patient details accuracy in (%) | | | | |
|--------------|---------------------------------|-------|-------|-------|-------|
| | HFOA | MTE | SBCC | HFEM | SPPA |
| 1000 | 78.72 | 82.82 | 66.47 | 65.2 | 92.6 |
| 2000 | 80.39 | 83.95 | 69.4 | 66.46 | 95.07 |
| 3000 | 82.34 | 84.3 | 70.94 | 68.35 | 95.87 |
| 4000 | 84.33 | 86.25 | 72.97 | 69.55 | 97.07 |
| 5000 | 86.91 | 87.02 | 73.87 | 61.11 | 97.71 |
| 6000 | 88.9 | 87.4 | 75.84 | 72.86 | 98.97 |
| 7000 | 90.92 | 88.53 | 77.31 | 73.79 | 99.97 |

4.2. Computation of Patient details precision: Patient details precision measurement is the ratio between the positive true Records and total true Records. The total true Records are calculated by the sum of positive true Records and false positive Records.

$$\text{Precision Measurement} = \frac{\text{True Positive Predictions}}{\text{True Positive prediction} + \text{False Positive Prediction}} \quad (2)$$

The below table 2 demonstrates the various measurement comparison of the patient details precision values between the existing HFOA, MTE, SBCC, HFEM and proposed SPPA

Table 2: Measurement of Patient details precision

| No.ofRecords | Patient details precision in (%) | | | | |
|--------------|----------------------------------|-------|-------|-------|-------|
| | HFOA | MTE | SBCC | HFEM | SPPA |
| 1000 | 80.31 | 76.75 | 67.72 | 64.56 | 93.77 |
| 2000 | 81.94 | 78.49 | 69.3 | 65.98 | 95.06 |
| 3000 | 82.42 | 80.83 | 71.5 | 67.24 | 96.07 |

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|------|-------|-------|-------|-------|-------|
| 4000 | 83.71 | 81.64 | 73.13 | 69.23 | 96.96 |
| 5000 | 85.82 | 83.93 | 74.27 | 71.7 | 97.33 |
| 6000 | 87.31 | 85.86 | 76.47 | 73.14 | 98.97 |
| 7000 | 89.12 | 87.59 | 77.62 | 74.86 | 99.34 |

4.3. Computation of Patient details recall: Patient details recall measurement is the ratio between the positive true Records and the sum of positive true Records and false negative true Records.

$$\text{Recall Measurement} = \frac{\text{True Positive Predictions}}{\text{True Positive Predictions} + \text{False Negative Predictions}} \quad (3)$$

The below table 3 demonstrates the various measurement comparison of the patient details recall values between the existing HFOA, MTE, SBCC, HFEM and proposed SPPA

Table 3: Measurement of Patient details recall

| No.ofRecords | Patient details recall in (%) | | | | |
|--------------|-------------------------------|-------|-------|-------|-------|
| | HFOA | MTE | SBCC | HFEM | SPPA |
| 1000 | 70.42 | 80.85 | 67.88 | 65.57 | 91.77 |
| 2000 | 71.91 | 82.82 | 70.3 | 67.77 | 93.76 |
| 3000 | 72.71 | 83.95 | 70.71 | 68.57 | 94.96 |
| 4000 | 75.04 | 85.16 | 72.31 | 69.24 | 95.44 |
| 5000 | 76.05 | 85.53 | 74.63 | 70.67 | 96.87 |
| 6000 | 76.69 | 87.06 | 75.88 | 71.76 | 98.03 |
| 7000 | 77.35 | 87.56 | 78.61 | 72.24 | 98.8 |

4.4. Computation of Patient details F1-Score: It's measured by the average sample values of patient details precision and patient details recall of the Records.

$$\text{F1-Score Measurement} = \frac{2 * (\text{Recall} * \text{Precision})}{(\text{Recall} + \text{Precision})} \quad (4)$$

The below table 4 demonstrates the various measurement comparison of the Patient details F1-Score values between the existing HFOA, MTE, SBCC, HFEM and proposed SPPA

Table 4: Measurement of Patient details F1-Score

| No.ofRecords | Patient details F1-Score in (%) | | | | |
|--------------|---------------------------------|-------|-------|-------|-------|
| | HFOA | MTE | SBCC | HFEM | SPPA |
| 1000 | 79.92 | 79.71 | 73.58 | 76.41 | 98.61 |
| 2000 | 78.43 | 77.74 | 71.16 | 74.21 | 96.62 |
| 3000 | 77.63 | 76.61 | 70.75 | 73.41 | 95.42 |
| 4000 | 75.3 | 75.4 | 69.15 | 72.74 | 94.94 |
| 5000 | 74.29 | 75.03 | 66.83 | 71.31 | 93.51 |
| 6000 | 73.65 | 73.5 | 65.58 | 70.22 | 92.35 |
| 7000 | 72.99 | 73 | 62.85 | 69.74 | 91.58 |

4.5. Computation of Computation duration: The computation duration is nothing but the time taken to calculate the prediction of two different patients.

$$\text{Computation Duration} = \frac{\text{No.of input samples}}{\text{Computation Speed}} \quad (5)$$

The below table 5 demonstrates the various measurement comparison of the patient details accuracy values between the existing HFOA, MTE, SBCC, HFEM and proposed SPPA

Table 5: Measurement of Patient details accuracy

| No.ofRecords | Computation Time (ms) | | | | |
|--------------|-----------------------|------|------|------|------|
| | HFOA | MTE | SBCC | HFEM | SPPA |
| 1000 | 8160 | 5745 | 8274 | 9771 | 1884 |

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|------|-------|------|-------|-------|------|
| 2000 | 8937 | 6302 | 8679 | 10155 | 2050 |
| 3000 | 9714 | 6859 | 9084 | 10539 | 2216 |
| 4000 | 10491 | 7416 | 9489 | 10923 | 2382 |
| 5000 | 11268 | 7973 | 9894 | 11307 | 2548 |
| 6000 | 12045 | 8530 | 10299 | 11691 | 2714 |
| 7000 | 12822 | 9087 | 10704 | 12075 | 2880 |

CONCLUSION

Health services are very affordable, accessible and meaningful. Furthermore, Machine learning has excellent communication with artificial technology and machine learning through a continuous installed computer process. It appreciates the need for infrastructure in any hospital. They work on establishing technology standards and accelerating innovation on the right track for all companies eager to explore the many benefits of communication manufacturing, logistics, healthcare, and automobile operating in industries including machine learning. The proposed Smart patient predicting algorithm (SPPA) was provided the better results while compared with the existing A hybrid fuzzy optimization algorithm (HFOA), Multi-fractal texture estimation (MTE), Segmentation based Chi-Square Fuzzy C-Mean Clustering (SBCC), hybrid feature extraction method (HFEM). These computations are very important in the medical field to diagnose the types of in-patients and the out-patients in the hospital. It is especially helpful for physicians to obtain information about the nature of patients and their health from the place where machine learning procedures were performed.

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