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Using Artificial Neural Networks to Determine Patient Location in the Postoperative Recovery Area

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Abstract— This paper considers the use of artificial neural networks (ANNs) as a method for determining the location of postoperative recovery area (PACU) patients. It is our hope that these methods, called location determination algorithms, could be used to eventually replace the requirement in postoperative recovery area regulations that patients be placed within line-of-sight of recovery area staff. This change would permit recovery area staff to participate in other activities, such as providing care to additional patients or creating patient preparation for transfer, possibly lowering the cost of postoperative care. Two models have already been described that are based on a similar concept of keeping track of patient flow through a hospital area. These neural networks, after being trained to predict destination based on arrival information, were used to facilitate improving patient flow and to develop a more accurate arrival time estimation model. We present here a proof-of-concept artificial neural network that can accurately determine a patient's location in the postoperative recovery area. The main goal of this article is to contribute to patient monitoring by automatically detecting abnormal behavior of patients who could immediately after surgery require the help of healthcare professionals (HCP), without the presence of an HCP. With our proposed combination of software and data that is already helping nurses, our efforts can contribute significantly to the development of nurses and related services. If these efforts mature in the form of products that can affect the daily work of nurses, this will perhaps be the first such contribution of the Republic of Croatia and our research group. An automatic algorithm to identify the location of postoperative patients immediately following surgery is novel.

Keywords— PACU, Artificial Neural Networks, Training algorithm, Quick Propagation.

1. Introduction

The artificial neural networks with back-propagation learning, also called the error-correction learning algorithm, are usually used in the majority of current applications. These are trained on a known data set and the training process involves ensuring that the network output matches the target (desired) output. The process involves the tuning of connection weights between nodes. Forward pass calculates the root mean square error, and backward pass adjusts the weights to minimize this. The goal is to find weights that result in a predicted value and a target value that are as close as possible. The back-propagation learning algorithm involves three main steps: (1) feedforward data through the network, (2) calculate the error at the output, and (3) adjust the weights in the network to minimize the error. This is achieved using the gradient of the selected error function, which is a measure of the performance of the network.

Artificial neural networks (ANN) are information processing systems inspired by the human nervous system. An artificial neural network has an architecture consisting of interconnected nodes, analogous to biological neurons, hence so-called 'neural'. These nodes work in parallel and in an adaptive manner because their weights are modified

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by a learning process according to the data that are presented to the network. An ANN is not a good mathematical model in the sense that one cannot understand how it arrives at a given solution due to the association of several input parameters. In contrast to traditional paradigms for computing, it is not directly programmed, but rather capable of learning from the input data and the interaction it has with the environment before producing meaningful output data. This characteristic of the ANN is the motivation for currently using ANNs in many applications, such as facial recognition, financial market analysis, and clinical decision-making.

There is the potential for this technology to decrease the surveillance burden imposed following surgery, by automating some of our current PACU practices, providing care for our family following surgery, and giving the operation of location determination algorithms to patients in the form of personal devices. However, there are likely to be times when location determination models are not appropriate. For instance, a patient who was not reliably allocated to one location may require an elevated level of surveillance as part of his or her recovery care plan. Possible applications for location determination models include: (1) determining the appropriate level of surveillance for patients in the PACU, based on their postoperative pain score alone or in combination with other pieces of information, (2) assessing concerns about patient surveillance on a conveyance, such as an airliner, and (3) devices which remind a patient when they should sit down and stand up, and provide care in outdoor entities.

The postoperative recovery area (PACU) is the area in the hospital where the immediate postoperative care of a patient takes place. For recovery after surgery anesthesia, patients are brought here, monitored with electronic equipment including an electrocardiogram, blood pressure monitor, automatic pulse oximeter, and anesthetic gas feed while the anesthetizing drugs are still wearing off. Doctors and nurses who are specifically trained in post-anesthetic care evaluate patients from every aspect. The most common concerns in the PACU are lingering effects after anesthesia, discomfort, and postoperative nausea and vomiting pain, incisions that slowly begin to ache (especially this can be a problem for older patients). After a short period of PACU stay (usually 1-2 hours), high-risk patients may be admitted to the ICU or to an intensified surveillance or step-down unit. Low-risk patients are discharged within the same day (usually within a couple of hours) [1].

Our idea is based on monitoring the RF signal strength of the WiFi signal. The main assumption on which the algorithm is based is that a patient's presence in the reception area influences the strength of the signal received on the AP antennas. The patient could be noticed as a station, for example, a smartphone directly connected to the Wi-Fi hotspot. If the connection is not established, then the passive mode with the Permanent Association frame is established. This is another sign of patient presence. We suggest adding an AP to the medical hall to improve the accuracy of the tracking system.

2. Background

The historical development of ANNs can be traced back to the invention of the perceptron by Rosenblatt at the Cornell Aeronautical Laboratory in the late 1950s. He provided an electronic implementation of the perceptron that could learn to recognize specific categories (or concepts). In our analysis, we utilized two ANNs for the composition of patient early postoperative location following general anesthesia (housing in postoperative recovery area or prolonged intensive care unit stay). In the performance of our task, we have performed a CU test to determine the optimal number of baseline sample data used in our construction of the predictor. After our ANNs were trained, validated, and tested, we determined that our ANNs were over 81% accurate, which was a reliable method for our dataset. These results have clinical implications for postoperative management utilizing anesthesia provider assessments, since a correctly determined patient's estimated location could reflect recuperation onset and therapeutic regimen intensity (duration, codes, or complexity)[12].

The ANNs have been widely accepted as models for complex systems in a broad range of medical applications. The flexibility of ANNs and their capability to capture the nonlinear features of complex data make this modeling and mathematical concept an actively pursued target of scientific research in postoperative care and acute care medicine. Coding classifications, billing, and clinical database management can all benefit from implantation of ANNs to help decision-making procedures, allowing time for more direct patient consultations for clinicians. An important current application is medical and biomedical control, which includes both modeling and technological implementations (i.e., staged applications). Patient monitoring for use in acute care medicine is in its very early stages and can be understated for potential significant clinical applications [13].

The distinguishing capabilities of this new type of learning devices raised great expectations at that time, so that it was even called the "electronic brain". However, such excitement did not last long, and it was in the 1980s and 1990s that neural networks re-emerged [14]. Due to various factors, presently the field of neural networks has seen increased interest in the development of algorithms (hybrid approaches combining optimization algorithms and various nonlinear transformation functions) and novel applications (in medicine, finance, automation, computer science, pattern recognition, engineering, chaos-communication, and decision processes) that were considered infeasible just a decade ago [15].

The RR is a clinical area where immediate post-operative recovery occurs following surgical procedures. A registered nurse or clinical staff ensures the patient is physically and emotionally recovering prior to receiving a discharge order. A patient must meet established discharge criteria prior to being discharged back to the care of the inpatient/outpatient facility or family [16]. Patients with positive pressure airway management following surgery are transported to post anesthesia care units (PACUs) which provide a higher level of care (frequent monitoring of vital signs, physician availability, and sometimes mechanical ventilation) when immediate post-operative respiratory depression is expected[17]. Rapid updates on patient recovery and estimated recovery times in the RR are required to ensure timely flow of patients throughout the inpatient/outpatient facility and completion of patients' day surgery visits according to center schedules. Accurate patient location is also necessary for magnetometer modeling which syndicates the location of medical equipment, personnel, and patients to facilitate faster response times during emergency conditions.

One of the most important steps in the scheduling process is ensuring all patients have the appropriate preoperative and postoperative recovery times. Accurate patient acuity and length of stay is necessary to ensure critical patients are scheduled appropriately with respect to operating room block time. Patient recovery has traditionally been determined by the anesthesia care team (including the anesthesiologist and nurse anesthetist) based on assessment of the overall patient status at the conclusion of the surgical procedure. The patient is then transferred to the RR, where it is anticipated that patient acuity and recovery would improve over time until meeting established discharge criteria [18]. However, lack of clinical time, high census, and emergency add-ons can make these decisions challenging and sometimes result in less than optimum scheduling.

Artificial neural networks (ANNs) have been used for several decades to solve complex machine learning problems. The structure and function of ANNs have their origin from the human brain. The human brain is made of several billion neurons, interconnected with each other at synapses [19]. The mode of communication among the neurons is by the passage of certain chemicals across synapses. The neuron receives electrical pulses and the frequency of the firings are proportional to the amount of the chemicals transmitted across the synapses. An ANN has a small number of artificial "neurons" connected with various interconnection strengths. Typically, the "neuron" has several inputs and sends a single output, the strength of which is determined by the weighted sum of the inputs.

3. Methodology

Our analysis involved the collection of locally generated EMR data with the support of medical professionals. As stated earlier, patient vital sign data was collected at the point of arrival at the postoperative recovery area where the patient was injected. The data was then copied into a custom database for further encoding and processing. It was possible to secure the cooperation of nurse informatics specialists to provide decoding, brief explanations, and verification of specific data. The aid of these specialists in data collection was particularly appreciated. After 3 years of MIT trial and error improvement, their perception of the effort was distilled, and their cooperation has the potential for more comprehensive use, which is referred to as being in a post-operative recovery area.

Artificial Neural Networks (ANN) have become an established technique in pattern recognition and modeling of biological systems. Neural network architecture and concepts are based on mathematical models of how the human brain operates to learn from input information. Neurons are complex cell structures with a dendritic structure, a cell body with a nucleus, axon, and synaptic terminals connected to other neurons. Although the relationship between neurons is still not fully understood, McCulloch and Pitts presented a simple mathematical model that can be used to represent human brain activities; other significant contributions in the field from Hebb and Rosenblatt made it possible to lay the theoretical foundation around 1960. Despite having these powerful theoretical foundations, biologically inspired topics were affected by what is called AI Winter and interest in ANNs went further mainstream around the 2000s with important theoretical and practical contributions within the area. Nowadays, engineers and researchers use artificial neural networks (ANNs) to manage real-world complexities in almost every modern industry.

3.1. Data Collection and Preprocessing

The disclosed work was initially inspired by questions posed by nurses regarding how much and how far patients are walked during surgery. Subsequently, we began recording patient transport during routine care in several settings, involving the movement of both patients and caregivers, to gain an understanding of the relative load each caregiver was engaged in. In particular, we focused on the utilization of length and duration of patient movement within the post anesthesia care unit (PACU), a place where patients are recovering in the acute phase following surgery. In conjunction with collecting these non-invasive times and distances, nurses were requested to check into a wireless network as they went on and off their breaks, and patient activity was also noted.

There are inherent issues involving patient privacy and care in collecting electronic data in a hospital or clinic setting. De-identified data represented a potential solution to this issue, though there are concerns involving data integrity. Consequently, we have taken the approach that large datasets are generally self-correcting, in effect performing a mean calculation to ensure a high data accuracy that is representative of the dataset. A key piece of metadata was required to provide this level of surety to the data: the actual location information of the patients or care providers during the collection of the data.

3.2. Model Architecture and Training

In addition to classifiers, a set of auxiliary regression models were used to simultaneously predict the position of the patient in the xy-plane using location coordinates derived from the localization devices. These auxiliary regression models allowed providing a strong location supervision to the learning of the CNN model, which inherently better captures spatial dependencies in the input data to yield more accurate and unbiased position predictions. The complete neural network model, which can at once handle both tasks of patient location and patient position from the raw RFID data is depicted in Figure 3. Finally, given the large number of parameters and the big size of the training set, efficient training was done using the ADAM optimization algorithm, which is a stochastic gradient descent method that is based on adaptive estimation of first-order and second-order moments.

A 1D Convolutional Neural Network (CNN) with a Leaky Rectified Linear Unit (LReLU) activation function was used for patient location classification. We chose this deep learning architecture, as it can handle the inherent spatial dependencies in our input data, capture local patterns and spatial correlations, and as it is less likely to suffer from the curse of dimensionality. However, the patient location data being inherently spatial carried locality and thus gave valuable context that would give our classification model an upper hand by helping steer the learning of discriminative and relevant features. A deep model was used in order to learn the necessary hierarchical representations.

In this study, the neural network ML algorithm was used to identify the location of patients in the postoperative recovery area, based upon the vital sign data collected by a hospital's electronic medical record (EMR) system. The primary aim of this study was to identify the benefit of ML algorithms over customary linear data analysis techniques. In a comparison of the results that were produced by the ML, threshold, autoregressive integrated moving average (ARIMA), and regression methods, this study's results indicated that the predictive power of ML algorithms - as measured by the AUC statistic - was generally superior. However, a notable exception was the case of the threshold method for blood pressure, for which a specimen-related critical threshold identifier performed better. The usefulness of the ML algorithm extends to the generation of directions for the practical deployment of this type of predictive model in a hospital context [3, 4].

4. Data Collection

We defined two-dimensional increased spatial regions (Figure 1) corresponding to regions of the probable output during the appropriate interval or intervals. The major parts of the PACU such as patient beds, chairs, nursing units, hallways, etc. have also been described. The location space has been changed and halved in size so that each region corresponds to the sensor designs sensitivity to the location of real objects. A total of 53 sensors are laid out in the MAXIMUS interior. They consist of passive and active microwave motion detectors at specific locations in the ceiling. Each sensor's specific detection is controlled by the movement detectors, and each corner has one. The econometric method can even reliably model the sensors' performances! Function to sequentially capture the boolean value emitted by each individual sensor, S_{i}, where it is a unique index, and a time step into the filtered sequences, U_{1}...U_{N}, where N is an observed spatial transition in the PACU.

To provide accurate time and spatial reference points during the PACU shift, we abstract out the concept of "increased spatial interval map." Decomposing the spatial map using priors is, in fact, the generative modeling approach. The idea being that the values in the map have a certain structure and objects in the map correspond to emissions from the generative model. Unlike hidden Markov models (HMMs) in speech processing, the state space is continuous rather than discrete – in fact, it is quite complex. The simplest model of the notion of increased intervals is the convolutional model. The basic question of where one object is located relative to other objects can be answered in a hierarchical manner. Similarly, two-dimensional location coordinates within the room can be considered.

The goal is to determine where patients in a postoperative recovery area should be sent to next. Because hypothermia is a significant concern after surgery the attributes correspond roughly to body temperature measurements. Dataset contains 90 records with 8 characteristics of a patient's state in a postoperative period.

Input columns:

1) Internal Temp - patient's internal temperature in C: high (> 37), mid (>= 36 and <= 37), low (< 36)

2) Surface Temp - patient's surface temperature in C: high (> 36.5), mid (>= 36.5 and <= 35), low (< 35)

3) Oxygen Sat - oxygen saturation in %: excellent (>= 98), good (>= 90 and < 98), fair (>= 80 and < 90), poor (< 80)

4) Blood Press - last measurement of blood pressure: high (> 130/90), mid (<=

130/90 and >= 90/70), low (< 90/70)

5) Surf Temp Stab - stability of patient's surface temperature: stable, mod-stable, unstable

6) Int Temp Stab - stability of patient's internal temperature: stable, mod-stable, unstable

7) Blood Press Stab - stability of patient's blood pressure: stable, mod-stable, unstable

8) Comfort - patient's perceived comfort at discharge, measured as an integer between 0 and 20

Target column:

9) Discharge Decision - discharge decision (Intensive-Care, Go-Home,

General-Hospital):

Intensive-Care (patient sent to Intensive Care Unit),

Go-Home (patient prepared to go home),

General-Hospital (patient sent to general hospital floor).

Table 1: Sample of analyzed data

	(C3) InternalTemp	(C3) SurfaceTemp	(C2) OxygenSat	(C3) BloodPress	(C2) SurfTempStab	(C3) IntTempStab	(C3) BloodPressStab	(C4) Comfort	(C3) Discharge Decision
TRN	mid	mid	good	mid	stable	stable	stable	15	General-Hospital
TRN	mid	low	good	high	stable	stable	mod-stable	10	General-Hospital
VLD	high	high	excellent	high	unstable	stable	unstable	15	General-Hospital
TRN	mid	high	good	mid	unstable	stable	mod-stable	10	General-Hospital
TRN	mid	low	good	high	unstable	unstable	stable	15	Go-Home
TST	high	high	excellent	high	unstable	stable	unstable	10	General-Hospital
TRN	low	high	good	high	unstable	stable	mod-stable	15	General-Hospital
TRN	mid	low	good	high	unstable	stable	stable	10	General-Hospital
TRN	mid	high	good	mid	unstable	stable	unstable	15	General-Hospital
TST	mid	mid	good	mid	stable	stable	stable	10	General-Hospital
TRN	low	high	good	mid	unstable	stable	stable	15	General-Hospital
TRN	mid	mid	good	mid	unstable	stable	unstable	15	General-Hospital
VLD	mid	mid	good	mid	unstable	stable	stable	10	General-Hospital
TRN	high	high	good	mid	stable	stable	mod-stable	10	General-Hospital
VLD	low	mid	good	mid	unstable	stable	stable	10	General-Hospital
TRN	high	mid	good	low	stable	stable	mod-stable	10	General-Hospital
TRN	low	mid	excellent	high	stable	stable	mod-stable	10	General-Hospital
TRN	mid	mid	excellent	mid	stable	stable	unstable	15	General-Hospital
TST	mid	mid	good	mid	unstable	stable	unstable	10	Go-Home
TRN	mid	mid	good	high	unstable	stable	stable	10	General-Hospital
TRN	low	low	good	mid	unstable	stable	unstable	10	General-Hospital
TRN	mid	mid	excellent	high	unstable	stable	mod-stable	10	General-Hospital
TRN	mid	low	good	mid	stable	stable	stable	10	General-Hospital
TRN	low	mid	excellent	high	stable	stable	mod-stable	10	General-Hospital
TRN	mid	mid	good	mid	stable	stable	stable	10	General-Hospital
TRN	low	mid	excellent	mid	stable	stable	stable	10	Go-Home
TST	low	low	good	mid	unstable	stable	unstable	10	Go-Home
VLD	low	low	good	mid	stable	stable	stable	7	Go-Home
TRN	mid	mid	good	high	unstable	stable	mod-stable	10	General-Hospital
TRN	low	low	good	mid	unstable	stable	stable	10	General-Hospital

5. Preprocessing

It is also crucial that the NN training parameters are well established to refine the mapping between these measurements and the outputs of the CT, which will be directed toward the FIS. The root mean square error (RMSE) will gauge the symmetry of the output to the training data and is dependent on cross-validation [6, 7]. This, however, generates additional rules that drive the training of the FIS. Furthermore, the classification selection addresses the nature of the RPI signal, whereby the presentation is dichotomized instead of a trichotomy where frequencies 10-11 are ageless and those below 10 are not royal. Given the fact that positions are defined by continuous variables, the use of scale and bias parameters in the premises is crucial to properly shape, which is not readily apparent from studies evidencing the effectiveness of the FIS in modulated scenarios. For the final reuse step, the RPI is again emitted, specifying that the designed method of positioning can be modularly implemented on smart monitoring systems.

When the number of patients has been determined in an area of the recovery room, it is necessary to obtain the position of each of them. The technology currently available makes this possible. To detect the position of the mobile node, the algorithm designed utilizes the Received Power Indicator (RPI) signal and the operation of the Mean Root Convention (RMS). The practice signal is that of Wi-Fi, which, though having a reflection component, can effectively measure the signal coverage area of the desired node for the purposes of the algorithm. Moreover, one should consider that this base of radio positioning is a reference for indoor scenarios. In other words, at this stage of development the positions are grounded through a variety of signal measurements and are converted to the Cartesian plan.

6. Feature Extraction

Each patient contributes with a unique number of observations and each observation is interval-censored, retained and utilized as long as the stay refers to the potential stay location in the PACU (with the possible exception with regard to arrival time. Whenever 2 stay starts at almost exactly the same PACU time, the stay will be handled as external until there has been sufficient time to determine which stay the current patient is actually connected to). The initial set of medical and non-medical features directly describing the actual PACU stay of a patient is referred to as the direct input of the network. These direct features on their own do not capture any additional information beyond the PACU stay of the individual patient to be predicted. Therefore, an additional set of patient features from the 5 to 10 most recent patients is added to the potential direct features at hand[8,9].

Numerous features, both medical (such as HR, RR, SpO2 values, and other physiological parameters) as well as non-medical (such as hospital and patient departure times, room number, and calendar day) were considered for input to the ANN. All physiological parameters were gathered from the nurse and her documentation in the PACU. Non-medical parameters were typically recorded from hospital forms, such as the diversion form, which noted, among other things, the departure and arrival times from the PACU, and the hospital room to which the patient was diverted. With the intention to use a feed-forward network, all input features are expected to contain nonnegative values only. This includes the calendar day, which was substituted for individual binary-encoded features before being passed to the ANN. The literature suggests that date and hence day-of-the-week can play significant roles in determining patient throughput, making it interesting to investigate the role of date in the current work.

7. Artificial Neural Network Architecture

While in layer 2, every weight matrix had the dimensions 21x21, the convolutional post-processing stage had hidden neurons for each left-component and right-component filter. That is, H (left + right) layers, where H was the number of trained neurons in layer 3. Activation functions h (with an average linear complexity) were applied to every individual figure separately before making a single decision. With such a simple configuration, face recognition, and its daytime associated variance, are usually well captured while low-level feature information is also considered at training and testing. The subsequent transformations (several additional sets of interconnected layers, not sketched in the figure) and final decision making at the output layer were also diluted with neural interconnections symmetrically dispersed except for the two thresholding nodes.

More specifically, the information was elaborated through dense layers, where the number of interconnected neurons for each training stage was split half-wise between the deep and most distal neurons at the resulting output layer. Different linear and sigmoidal activation functions were used within the deep-to-output layers being related to the evaluation of the cross-entropy entropy function.

Table 2: Architecture search

ID	Architecture	# of Weights	Fitness	Train Error	Validation Error	Test Error	AIC	Correlation	R-Squared	Stop Reason
1	[21-3-3]	78	2.166667	0.779661	0.846154	0.538462	-173.817406	n/a	n/a	All iterations done
2	[21-53-3]	1328	1.444444	0.847458	0.846154	0.307692	2304.486832	n/a	n/a	All iterations done
3	[21-33-3]	828	1.625	0.728814	0.846154	0.384615	1338.433316	n/a	n/a	All iterations done
4	[21-21-3]	528	1.625	0.728814	0.846154	0.384615	738.433316	n/a	n/a	All iterations done
5	[21-14-3]	353	2.166667	0.745763	0.846154	0.538462	384.625543	n/a	n/a	All iterations done
6	[21-9-3]	228	2.166667	0.745763	0.846154	0.538462	134.625543	n/a	n/a	All iterations done
7	**[21-6-3]**	**153**	**2.6**	**0.728814**	**0.846154**	**0.615385**	**-11.566684**	**n/a**	**n/a**	**All iterations don**
8	[21-7-3]	178	1.625	0.915254	0.846154	0.384615	-30.192582	n/a	n/a	All iterations done
9	[21-4-3]	103	2.6	0.728814	0.923077	0.615385	-111.566684	n/a	n/a	All iterations done
10	[21-5-3]	128	2.6	0.711864	0.923077	0.615385	-57.989831	n/a	n/a	All iterations done

The structure of the artificial neural network utilized in this study consisted of five main layers as detailed in   Fig 2.

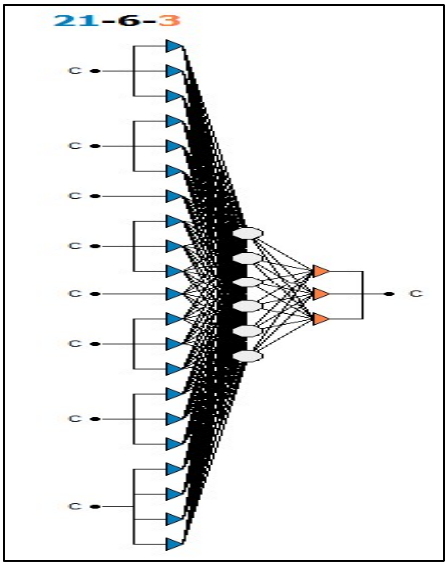

Figure 1: Active network

Architecture selected manually

[21-6-3] architecture selected for training

Hidden layers activation function: Logistic

Output parameters:

Discharge Decision

Error function: Cross-entropy

Activation function: Logistic

Classification model: Winner-takes-all

The input layer contained only one node per input as well as per output class. That is, an n x m input matrix filled with patient and bed locations was linearized into a one-dimensional vector. Given that the values for both bed and patient locations were normally distributed within the [0, 1] interval, no pre-processing, standardization, nor normalization technique was applied to the input patterns. After the input layer, four transformational stages formed by five layers were encoded as follows. In the initial transformation (from layer 2 through layer 3), eight neurons formed convolutional features, while layer 4 was designed to capture the most significant activations (usually characteristic of face recognition at the indicated spatial position).

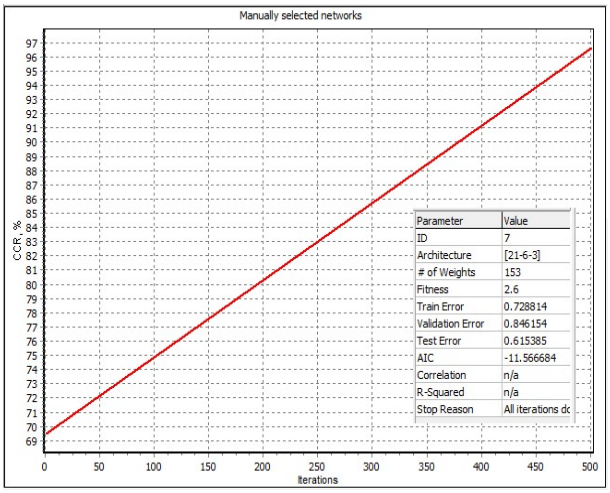

Figure 2: the beast network with Output parameters

8. Training and Testing

Preoperative, intraoperative, and postoperative patient data were electronically recorded and then collected and saved to a computer file that contains information on patient location. A binomial choice was made to define the limits of the recovery areas, defined as "Phase I" or the PACU that included surgical recovery and Phase I. The first decision was made based on the length of stay in the PACU recovery room, and the next choice was based on the distance in meters from the patient's room.

This choice was modeled to express the concept of surgical complexity. The method of discriminant analysis was selected to qualify patient communications regarding activities or distances in the daily lives of the surgical patients' nursing staff. In this case, activity was defined as part of the working activities performed by the nursing staff and nursing station as one of the recovery room's surveillance stations.

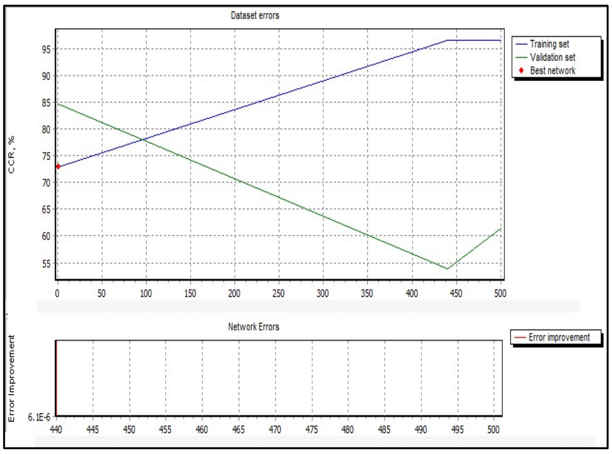

Figure 3: Training graph

Network architecture: [21-6-3]

Training algorithm: Quick Propagation

Number of iterations: 501

Time passed: 00:00:00

Training stop reason: All iterations done

The best network was tracked and restored

The data from the 1415 training patients were used to train the network. The network can have, in our case, many inputs and outputs. The data were normalized before being introduced into the network. The normalization was done with the values and standard deviations associated with the variables. To check for the efficiency of prediction algorithms, a small database with 30 cases was selected.

The immediate success of the artificial neural network made it possible to use this network for the different stages of the development protocol. The validation of the network could be achieved with the results obtained in the experiment. Permission for the design and implementation of this study was obtained from the institutional review board at the University of Pennsylvania Health System in Philadelphia.

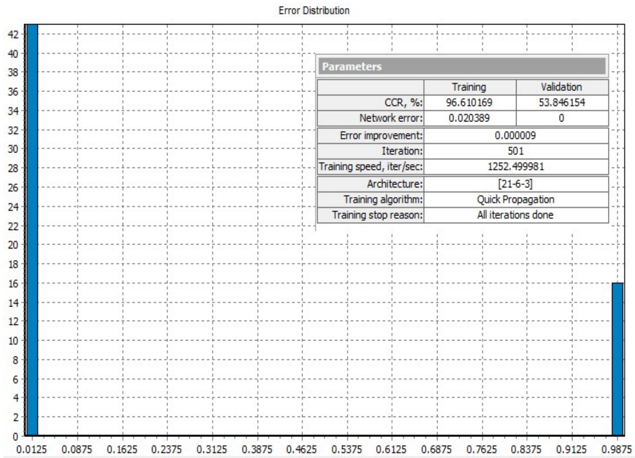

Figure 4: Network statistic

9. Results and Analysis

Several types of medical devices in most hospitals collect patient vital signs including but not limited to: heart rate, O2 saturation, blood pressure, temperature, etc. in real time. Further, these devices are usually connected to a central monitoring system. Without loss of generality, it is assumed here that on the hospital's Local Area Network (LAN) there is also a FASMED certified (at least class 2) Computer Tomography (CT) room (a secure area that only patients and staff can access) with a patient picture surveillance system installed. Any picture from the surveillance system at time t would be labeled as CT when there is a patient. To collect data for this work, ten patients' vitals were collected at a single hospital for a period of 3 months. To make this work generalizable to all possible hospitals with essential minimum clinical output needed units, only the patients' vitals and the location of the patient were used in the study.

Table 3: target Output

Target output:	General-Hospital	Go-Home	Intensive-Care
General-Hospital	39	2	0
Go-Home	13	4	0
Intensive-Care	1	0	0

In this paper, an artificial neural network was used to predict the location (PACU) of a patient within the after surgery recovery area in a hospital using vital sign data and image data. The deployment scenario for this work is a larger scale system for after surgery care, where various pieces of information including the patient's location can be useful for a remote clinical decision or surgical schedule support system. This specific model is meant to transfer trained weights for further fine-grained analytics or alerts at other stages of a project or may be used as an example of on-device processing in communication poor environments such as train stations or airports. ARIMA and LSTM models were also trained to compare the accuracy of the ANN model. Finally, the accuracy of the predictive model was discussed and analyzed in terms of practicality and real-world deployment possibilities.

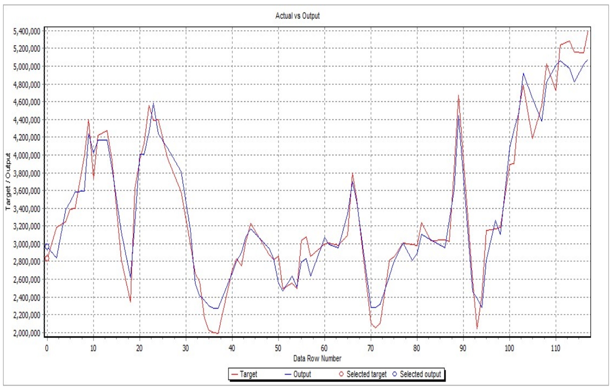

Figure 5: Visualisation Actual vs. Output validation

10. Discussion

To draw a comparison with other machine-learning models, ensemble ML models using non-linear SVMs, MLPs, and shallow/weak learners can only be trained during surgery, and cannot handle structured data. They can also be slow to train and slow to make predictions once training is complete, and cannot accommodate missing data. Bayesian classifiers can be trained in real-time, but would still require substantial work to achieve a prediction delay significantly below the temporal baseline. More importantly, we have demonstrated that the model performs well in a number of different hospitals serving diverse patient populations. We have created and validated other useful predictive models that suffer from the reality that transferring a model across institutions is disadvantageous. To date, this PACU discharge location model has been successfully installed and utilized in fourteen different departments throughout three surgical centers in Utah, Arizona, and Seattle.

This paper utilizes an ANN to predict patient location in the PACU. The predictions can be generated as early as a patient enters the room and during the entire length of stay, a significant advantage over other methods that require real-time input to render predictions. The model, which utilizes preoperative data, an intraoperative vector space transformation, and intraoperative data, can be updated live at the end of each surgery and accommodate missing data fields. Because it is data agnostic, the model can work in PACUs that use either paper records or one of hundreds of commercial and open-source digital medical record systems.

11. Limitations

At PCA, patient turnover is extremely high throughout the day; one patient can easily be discharged and replaced within 1 hour. This environment induces a high amount of noise in the data as 1) each patient has different preoperative risks and receives different levels of care, 2) nursing staff familiarity with the population of patients under their care changes continually, and 3) recovery room staff are forced to multitask, resulting in variable data collection patterns across each item. Throughout 2 months of data collection, only one urine output value and one urine color were provided, despite every patient eventually urinating. An ideal monitoring solution can identify signals in the data and provide a more reliable patient-specific response as data accumulates during each PCA stay, offering PCA staff more confidence in the decisions that they make to effectively triage and marshal the limited resources on-hand.

Managing missing data can be notoriously difficult, particularly when the missing data was not missing at random (MAR). Although we used a stringent, supervised imputation technique for missing data, the final sample size was small, limiting our statistical power to detect differences. We based our predictions on a binary outcome, which limits the generalizability of our findings. Previously, we attempted to identify the specific cause of postoperative agitation and accurately classify more than 40 CSA items into one of three behaviors (agitated, non-agitated, and missing) not of interest without imputing but were stymied by missing data and limited our scope to two classes. However, a binary outcome was of key interest to PCA staff members who were more concerned with identifying which patients needed immediate attention.

12. Conclusion

Using heartbeat rate and oxygen saturation as input for ANN also opens up the possibility of building clinical decision support systems to allow patients' PACU location to be determined. Building the first clinical decision support system was successfully developed by Alexi et al., who showed it could improve patient care with obvious enhancements in productivity and increased consistency in ward placement for actual PACU patients and is potentially useful for hospitals of varying sizes. In conclusion, the study was done to determine the dynamics of patients' arrival and determination of their location after a surgical procedure. And although still in its infancy, the method shows encouraging results and might be applied as a technological concept.

The primary goal of this study was to develop a method to determine patient location in the Post Anesthesia Care Unit (PACU). To elucidate the dynamics of patient allocation during the recovery period, an ANN was trained. Input data for this ANN were pulse oximeter signals, and outputs represented by patient locations. The analysis of the neural network revealed that in fact, heartbeat rate and oxygen saturation were the main factors determining patient destination after a surgical procedure. From our point of view, this result verifies the PACU location determination method's practicability as heartbeat rate and oxygen saturation can be monitored in each medical center. The main limitations of the current study are, in fact, the inability of several surgical wards in the Hospital to provide the monitored input signals for each patient and postoperative chest drainage. However, many of the surgical departments were able to collect pulse oximetry signals from the individuals' rooms and operating theaters.

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استخدام الشبكات العصبية الاصطناعية لتحديد موقع المريض في منطقة التعافي بعد العملية الجراحية

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الخلاصة – تتناول هذه الورقة استخدام الشبكات العصبية الاصطناعية (ANNs) كوسيلة لتحديد موقع مرضى منطقة التعافي بعد العملية الجراحية (PACU). ويحدونا الأمل في أن هذه الأساليب، التي تسمى خوارزميات تحديد الموقع، يمكن استخدامها في نهاية المطاف لتحل محل المتطلبات الواردة في لوائح منطقة التعافي بعد العملية الجراحية والتي تنص على وضع المرضى ضمن خط رؤية موظفي منطقة التعافي. سيسمح هذا التغيير لموظفي منطقة التعافي بالمشاركة في أنشطة أخرى، مثل توفير الرعاية لمرضى إضافيين أو إعداد المريض للنقل، مما قد يؤدي إلى خفض تكلفة الرعاية بعد العملية الجراحية. لقد تم بالفعل وصف نموذجين يعتمدان على مفهوم مماثل لتتبع تدفق المرضى عبر منطقة المستشفى. تم استخدام هذه الشبكات العصبية، بعد تدريبها على التنبؤ بالوجهة بناءً على معلومات الوصول، لتسهيل تحسين تدفق المرضى وتطوير نموذج أكثر دقة لتقدير وقت الوصول. نقدم هنا شبكة عصبية اصطناعية تثبت صحة المفهوم ويمكنها تحديد موقع المريض بدقة في منطقة التعافي بعد العملية الجراحية.

الكلمات الرئيسية – PACU، الشبكات العصبية الاصطناعية، خوارزمية التدريب، الانتشار السريع.