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# An Automatic System Based Linear Discriminant Analysis Artificial Neural Network For Detecting Of Post-Operative Patient Status

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***Abstract*—In medical literature, the detecting of post-operative patient status is very important topic. In this paper, An Automatic System based Linear Discriminant Analysis (LDA) and Artificial Neural Network (ANN) for Detecting of Post-operative Patient Status (A_LDA_ANN_DPPS) is introduced. This automatic system consists of three stages, which are feature extraction and feature reduction stage, classification stage, and testing stage. In feature extraction and feature reduction stage, the Linear Discriminant Analysis (LDA) is used for reduce the data dimensionality and also to clear out some irregularitises from the data. In classification stage, a ANN classifier is used for classification of reduced features in feature extraction and feature reduction stage. In this study, post-operative patient dataset obtained uci repository is used to create this A_LDA_ANN_DPPS system to determine based on hypothermia condition, whether patients in a post-operative recovery area should be sent to intensive care unit, general hospital floor or go home. In testing stage, the correct classification accuracy of this A_LDA_ANN_DPPS system is calculated. The testing results show that the correct classification accuracy of this A_LDA_ANN_DPPS system was obtained about 84.44 % high performance.**

***Keywords—Automatic detecting system; Expert Systems; Linear Discriminant Analysis (LDA); Artificial Neural Network (ANN) classifier.***

## 1. Introduction:

In medical literature, the detecting of post-operative patient status is very important topic. What to do after surgery for patients are presented in the following items [1-3]:

*a. Come self-rooms:* In almost every hospital after operation to remove the patient's room has its own recovery after operation in patient care specialist in this room have seen is the staff officer. Early postoperative complications that can show all the tools necessary to deal with are in this room. Patients are sent to the room a few hours and several days if necessary, be kept in their own recovery room. *b. Position will be in bed:* Operating room after leaving the surgical patients usually flat is credited children belly, big is back later admitted are operative as a result the patient's blood pressure has dropped, stock cases, the patient's bedside foot print level higher will be removed. This is the way to deal with increased blood flow and blood pressure: Also raised. Neck and chest operation, the patient is placed in half sitting on the bed. The influence of anesthesia after the patient's exact position on the bed to change constantly, in bed, arms and legs to play the harp is. Blood clots in veins in the end, this possibility is avoided.

*c. Air cylinders:* Anesthesiologists in many surgical patients will extend deep into the mouth and throat do not have a duty to make the air will place a tube. This will prevent the patient swallowing his tongue or the lungs from the outside does not prevent free air flow in any other way. This tube will remain in place until the patient himself. When it comes to their patients with a cough or a hand of this tube can be removed. These airways are the tubes and the mouth with a small black plastic tube in the windpipe is as easy as can be. *d. Surf:* In modern operation patients to get out of bed as quickly as possible and are expected to navigate and is recommended. In this way complications of liver diseases are prevented. Most patients are operated on a day immediately after operation can get out of bed and walk. Others the second or third day after the operation can get up and around. In some cases, patients after operation and sometimes longer than a week removed from the bed. *e. Gastric tubes:* Swelling of the stomach after gastric operation, and patients often occurs too close for comfort, and pains or par. To avoid this, a tube into the stomach through the nose is lowered and there shall be a day or two. Air and gas from the stomach remain empty for now, these tires provide a suction device is connected to the tube sometimes. *f. Taking food and drinks:* Juicy stuff, especially in patients receiving preoperative are prohibited. After operation, these patients become very thirsty. Patients with stomach or intestinal operation and they did a few hours after operation than they are given little water or tea. (Stomach or screaming kept their been operated patients, two or three days of food and beverages are not. These syringes with the vessel via the fluid with the feed.) This system is being applied is not such ill operation a day after a small amount of light and soft foods are given. However, after three or four days are spent in the normal regime.

*g. Probes used:* Can not be one or two days after the operation urine is a common event. This is usually used anesthesia times ribs and lower abdomen, in women's bodies and the ongoing operation is a case of breech. Swollen and empty a bladder that can not be so hard to avoid discomfort to bring a certain period of time with a rubber tube to the bladder are installed. In some cases, these final few days are left in place. *h. Narcotics:* After operation, each patient is more or less inevitable that this will attract pains pains to eliminate the resort to be narcotic. Builder narcotic pain relief or sedative drugs, if necessary, until two days after an operation, can be given every few hours. The patient does not use these drugs than is recommended. Because they may delay healing. In this case there is no fear of narcotic addiction can be. As to why it will improve a patient's addiction within a few days does not occur. *i. Antibiotics:* Doctor delay postoperative recovery because of an infection if it considers the possibility of injection or oral antibiotics to be given to patients. The patient's doctor to any sensitive or allergic to the antibiotic drugs that are very important to notice. Antibiotic drugs, a majority of patients are not sensitive or allergic to the drug did not provide a. *j. Blood transplants:* It is loss any significant amount of blood in operation.

*k. Enemas:* Intestine after abdominal operation for the first four, five or six days are not working well. Should be unable to get out worry. To correct this situation the operation of the third, fourth or fifth day is recommended in the enema. *l. Dressings for wounds:* Be different depending on the type of surgical wound surgery. Drainage after surgery for an inflamed wound dressing every day or two days is required. Clean, tightly closed with surgical wounds with forceps or stitches will be the sixth, seventh or eighth day until the dressing is not necessary. Pains do not usually make dressing. However, if quality dressings pains to make the operator be given a sedative or narcotic drugs recommended. m. Sutures and forceps. As noted above, the operation of six stitches, and forceps, are removed after seven or eight days. Pliers for the removal of stitches and pains and discomfort are minimal. n. Blood tests: After operation the patient's blood chemistry to be carefully measured and recorded are very important. Chemical imbalances impede the patient's postoperative recovery. So patients often are taken and analyzed for blood is sent to the laboratory.

In literature, there are many studies about detecting of post-operative patient status. In one of these studies [4], Principle Component Analysis (PCA) and similarity classifier methods were used for detecting of post-operative patient status and mean classification accuracy of 62.7% was obtained.

In this study, An Automatic System based Linear Discriminant Analysis (LDA) and Artificial Neural Network (ANN) for Detecting of Post-operative Patient Status (A_LDA_ANN_DPPS) is introduced. This automatic system consists of three stages, which are feature extraction and feature reduction stage, classification stage, and testing stage. In feature extraction and feature reduction stage, the Linear Discriminant Analysis (LDA) is used for reduce the data dimensionality and also to clear out some irregularitises from the data. In classification stage, a ANN classifier is used for classification of reduced features in feature extraction and feature reduction stage. In this study, post-operative patient data set obtained uci repository is used to create this A_LDA_ANN_DPPS system to determine based on hypothermia condition, whether patients in a post-operative recovery area should be sent to Intensive Care Unit, general hospital floor or go home. In testing stage, the correct classification accuracy of this A_LDA_ANN_DPPS system is calculated. The testing results show that the correct classification accuracy of this A_LDA_ANN_DPPS system was obtained about 84.44 % high performance.

## 2. The Linear Discriminant Analysis Method for Feature Reduction

The Linear Discriminant Analysis (LDA) [5], [6] is used for class specific discriminative. This LDA method benefits supervised learning to find a set of base vectors. They are represented by $\boldsymbol{y_k}$. These $\boldsymbol{y_k}$ vectors are ratio of the between- and withinclass scatters of the training sample set. They are maximized. The following generalized eigenvalue problem should be solved for find $\boldsymbol{y_k}$ base vectors,

$$T_{opt} = \underset{y}{\arg\max} \frac{\left|T^T G_C T\right|}{\left|T^T G_V T\right|} = [y_1, y_2, ..., y_Z] \quad (1)$$

In there, $\{y_k | 1 \le k \le Z\}$ are the Linear Discriminant Analysis (LDA) subspace base vectors. $Z$ is the dimension of the subspace. $Gc$ and $G_v$ are the between and within class scatter matrices. These matrices can be given as below:

$$G_C = \sum_{k=1}^{b} J_k (\mu_k - \mu)(\mu_k - \mu)^T \quad (2)$$

$$G_v = \sum_{k=1}^{b} \sum_{e_u \in D_k} (e_u - \mu_k)(e_u - \mu_k)^T \quad (3)$$

where, $b$ is the number of classes and $e \in R^N$ is the data sample. $D_k$ is the set of samples with class label $k$. $\mu_k$ is the mean for the all the samples with the class label $k$. $J_k$ is the number of samples in the class $k$. The base vectors $\boldsymbol{y_k}$ sought in Eq.(1) are the first $Z$ largest eigenvalues $\{\psi_k | 1 \le k \le Z\}$, if $G_v$ is non-singular. The base vectors $\boldsymbol{y_k}$ can be obtained its representation in LDA subspace by a simple linear projection $T^T x$ for a given test sample *e* due to the LDA base vectors are orthogonal to each other.

The readers can acquired more knowledge about the Linear Discriminant Analysis (LDA) from [5], [6].

### 3. Artificial Neural Networks

Biological neurons are similar to nerve cells. By establishing links between artificial neurons that constitute the neural network. As in biological neurons, artificial neurons as the input signals they receive, collect and process these signals and outputs that are forwarded to the department [7], [8].

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Consists of five parts of a neuron; ◦ Inputs ◦ Weight ◦ Merge function ◦ Activation functions ◦ Outputs

The block diagram of a neuron can be given as below in Fig.1:

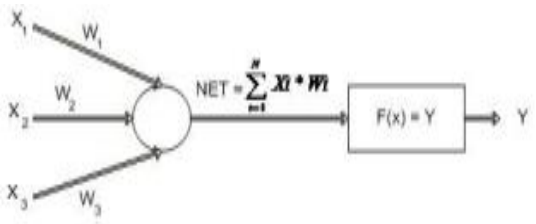


**Fig.1.** Block diagram of a neuron.

- Inputs The data are input neurons. Inputs into neural cells can come from other cells, such as may come directly from the outside world. Biological data from this input, as in the nerve cells to be collected is sent to the neuron nucleus.
- Weight Entered the information into neurons before reaching the core came over by multiplying the weight of the connection is forwarded to the kernel. In this way, the impact of inputs can be adjusted for producing of output. The value of these weights with positive, negative or zero. Figure out the weight of zero on the input does not have any effect.
- Merge Function A merge function is multiplied by the weight of neurons to gather input from those cells is a function that calculates the net input. The function of net input is given at Eq.(4):

$$\text{NET} = \sum_{i=1}^{N} Xi * Wi \quad (4)$$

- Activation Function Merge (collection) function to create the output of the NET total cells are transmitted to the activation function. Nonlinear activation function is usually a function is selected. Artificial neural network, which is a feature of "non-linear" activation function nonlinearity characteristics come from. Activation function is chosen to be considered a derivative of the function of the other point is that it is easy to be calculated. Activation function in the feedback networks are used for the calculation of the derivative does not slow down easily calculate the derivative of a function is selected.

The readers can acquired more knowledge about the Artificial Neural Network (ANN) from [7], [8].

### 4. Application of Automatic System based Linear Discriminant Analysis (LDA) and Artificial Neural Network (ANN) for Detecting of Post-operative Patient Status.

In here, A_LDA_ANN_DPPS is presented. This automatic system consists of three stages, which are feature extraction and feature reduction stage, classification stage, and testing stage.

The Automatic System based Linear Discriminant Analysis (LDA) and Artificial Neural Network (ANN) for Detecting of Post-operative Patient Status (A_LDA_ANN_DPPS) used in this paper is given in Fig.1.

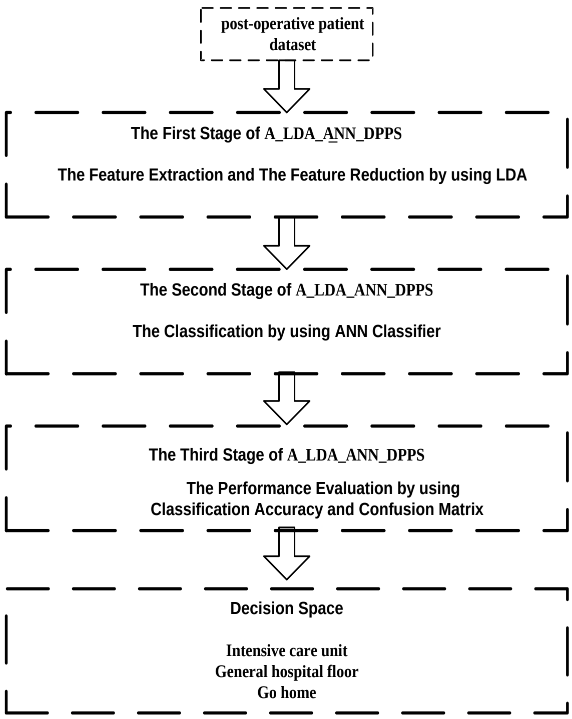


**Fig.1.** The blockdiagram of the A_LDA_ANN_DPPS for detecting of post-operative patient status used in this study.

This automatic diagnosis system consists of three stages: a) The feature reduction by using Linear Discriminant Analysis (LDA) method, b) The classification by using ANN classifier, and c) The performance evaluation of this A_LDA_ANN_DPPS automatic system for detecting of post-operative patient status by using classification accuracy and confusion matrix methods respectively [9-22].

In classification stage, a ANN classifier is used for classification of reduced features in feature extraction and feature reduction stage. In this study, post-operative patient data set obtained uci repository is used to create this A_LDA_ANN_DPPS system to determine based on hypothermia condition, whether patients in a post-operative recovery area should be sent to intensive care unit, general hospital floor or go home.

***a) The feature extraction and feature reduction stage:*** In feature extraction and feature reduction stage, the Linear Discriminant Analysis (LDA) is used for reduce the data dimensionality and also to clear out some irregularitises from the data.

In this experimental studies, the post-operative patient dataset is used for A_LDA_ANN_DPPS automatic system for detecting of post-operative patient status. This post-operative patient dataset was acquired from the UCI Repository of Machine Learning Databases [23]. The features of post-operative patient dataset can be summurized as below:

This post-operative patient dataset has 90 sample and 8 attributes. These attributes can be given in Table 1:

**Table 1.** The attributes of post-operative patient dataset used for the A_LDA_ANN_DPPS.

| **Number and name of attributes** | |
|---|---|
| 1 | L-CORE (patient's internal temperature in C): high (> 37), mid (>= 36 and <= 37), low (< 36) |
| 2 | L-SURF (patient's surface temperature in C): high (> 36.5), mid (>= 36.5 and <= 35), low (< 35) |
| 3 | L-$O_2$ (oxygen saturation in %): excellent (>= 98), good (>= 90 and < 98), fair (>= 80 and < 90), poor (< 80) |
| 4 | L-BP (last measurement of blood pressure): high (> 130/90), mid (<= 130/90 and >= 90/70), low (< 90/70) |
| 5 | SURF-STBL (stability of patient's surface temperature): stable, mod-stable, unstable |
| 6 | CORE-STBL (stability of patient's core temperature) stable, mod-stable, unstable |
| 7 | BP-STBL (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) |
| 9 | Decision ADM-DECS (discharge decision): I (patient sent to intensive care unit), S (patient prepared to go home), A (patient sent to general hospital floor) |

Class distribution of this post-operative patient dataset used for the A_LDA_ANN_DPPS.

can be given in Table 2:

**Table 2.** Class distribution of this post-operative patient dataset used for the A_LDA_ANN_DPPS.

| ***Class value*** | ***Number of samples*** |
|---|---|
| 1 patient sent to general hospital floor | 64 |
| 2 patient prepared to go home | 18 |
| 3 patient sent to intensive care unit | 8 |

As shown that number of samples of patient sent to general hospital floor, number of samples of patient prepared to go home and number of samples of patient sent to intensive care unit are 64, 18, and 8 respectively. Totally, there are 90 samples in this post-operative patient dataset.

The feature extraction is most important stage of a pattern recognition process [9-27]. The feature extraction and the feature reduction processes are performed in feature reduction stage of the A_LDA_ANN_DPPS automatic system for detecting of post-operative patient status. For this goal, the post-operative patient dataset mentioned above was composed. The dimension of this post-operative patient dataset, which has 8 features, was reduced to 4 features using Linear Discriminant Analysis (LDA) method mentioned in Section 2.

***b) The Classification Stage:*** The reduced features are given to inputs of ANN classifier that is mentioned in Section 3, in classification stage of the A_LDA_ANN_DPPS automatic system for detecting of post-operative patient status. The training parameters of artificial neural network classifier used in this study can be given on Table 3.

**Table 3.** Artificial neural network structure and training parameters.

| | |
|---|---|
| ***Number of layers*** | 3 |
| ***The Number of Layer Nerons*** | Input: 4, Hidden Layer: 8, Output: 1 |
| ***Initiate weights and biases*** | The Nguyen-Widrow method |
| ***Aktivation functions*** | Log-sigmoid |
| ***Learning rule*** | Back propogation |
| ***Mean square error*** | 0.00000001 |

These values, for example, the number of hidden layers, the number of cells in hidden layers, learning rate and the value of the activation function, after several tries, could have been selected for the best performance.

***c) The testing stage:*** In this stage, the performance evaluation of this A_LDA_ANN_DPPS automatic system for detecting of post-operative patient status is performed by using classification accuracy and confusion matrix methods respectively.

It was done the experimental studies on the post-operative patient dataset mentioned in Section 4 to evaluate the robustness of A_LDA_ANN_DPPS automatic system for detecting of post-operative patient status. It was compared results of this A_LDA_ANN_DPPS system with previous the results reported by earlier methods [1], [2], [4].

In these experimental studies, 50-50 % partition was used for training-test of A_LDA_ANN_DPPS automatic system for detecting of post-operative patient status. 45-45 samples were used for training and testing of A_LDA_ANN_DPPS automatic system for detecting of post-operative patient status respectively.

The obtained results of this A_LDA_ANN_DPPS automatic system for detecting of post-operative patient status will be demonstrated by using classification accuracy analysis performance evaluation technique in this section.

In here, the correct detecting of post-operative patient status was computed for obtaining of results of classification accuracy analysis for A_LDA_ANN_DPPS automatic system for detecting of post-operative patient status in this study by using Eq.(5) [1], [2], [4].

$$diagnosis\_accuracy(C) = \frac{\sum_{k=1}^{|C|} assess(c_k)}{|C|}, \quad (5)$$

$$c_k \in C$$

$$assess(c) = \begin{cases} 1, & if \quad classify(c) = c.d \\ 0, & otherwise \end{cases}$$

where, $C$ is the set of database to be classified, which is the test set. $c_k \in C$, $c_k.d$ is the class of item $c$ . The classify($c_k$) returns the classification of $c_k$ by ANN classifier.

The obtained classification accuracy by using A_LDA_ANN_DPPS automatic system for detecting of post-operative patient status is given in Table 4.

**Table 4.** The obtained classification accuracy by using A_LDA_ANN_DPPS.

| Decision Space | The number of true classificaton | The number of false classificaton | The obtained classification accuracy (%) |
|---|---|---|---|
| 1 patient sent to general hospital floor | 28 | 4 | 87.50 |
| 2 patient prepared to go home | 7 | 2 | 77.77 |
| 3 patient sent to intensive care unit | 3 | 1 | 75 |
| **Total** | **38** | **7** | **84.44** |

In there, the confusion matrix includes knowledge about actual and predicted classifications realized by using a classification system. The performance of this classification system is generally evaluated by using the data in the matrix. The obtained confusion matrix by using A_LDA_ANN_DPPS for 45-45 % training-test partition are given in Table 5.

**Table 5.** The obtained confusion matrix by using A_LDA_ANN_DPPS.

| Output/Desired | 1 patient sent to general hospital floor | 2 patient prepared to go home | 3 patient sent to intensive care unit |
|---|---|---|---|
| 1 patient sent to general hospital floor | 28 | 1 | 3 |
| 2 patient prepared to go home | 1 | 7 | 1 |
| 3 patient sent to intensive care unit | 1 | - | 3 |

## 5. Discussion and Conclusion

In this study, the Linear Discriminant Analysis (LDA) and ANN classifier was applied to detecting of post-operative patient status. Then, the most accurate learning methods was evaluated. It is concluded that the A_LDA_ANN_DPPS automatic system for detecting of post-operative patient status obtains very promising results in classifying the possible post-operative patient status. This statement of A_LDA_ANN_DPPS automatic system for detecting of post-operative patient status is clearly seen from the above results.

It is believed that the used A_LDA_ANN_DPPS automatic detecting system can be very helpful to the physicians for their final decision on their patients. The physicians can perform very accurate decisions by using such an efficient tool.

According to these results, the LDA and ANN classifier based a learning method can assist in the detecting of post-operative patient status. In future studies of detecting of post-operative patient status, different feature extraction and classifier methods will use for increasing of correct accurate.

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