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# Mortality Prediction in ICU Using Artificial Neural Networks

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**Abstract:** Intensive Care Unit (ICU) death rate prediction supported artificial neural network, patients WHO have important unwellness and injury can get admitted to the unit. The dying rate for sufferers admitted to the unit can vary from Associate in Nursing underlying illness with a dying rate as low as one in twenty sufferers admitted for non-compulsory surgical operation and as excessive as one in 4 sufferers with metabolic process diseases. Artificial Neural Networks facilitate health care management selections, improve care and cut back value at same time by exploiting the applications of ANN within the care department. It helps to alter, minimize errors and predict additional correct diagnoses for the diseases or injuries that may cut back patients' risk of hospitalization supported given knowledge. Associate in Nursing empiric study was conducted with 4000+ adult patients from 100+ ICUs. The patients with  $\geq 1$  organ failure are forty sixth. Patients without infection receiving antibiotics stand for an hour. There have been 500+ deaths and 183 discharges from the unit. In 1627 patients admitted among twenty four h of the study day, the standardized mortality quantitative relation was zero.67. We have a tendency to develop our model exploitation of a synthetic Neural Network to predict the death rate of sick patients supported by their diseases, injuries, and medical records. This can additionally facilitate managing the unit beds in hospitals throughout the Associate in Nursing emergency.

**Keywords:** Image Processing, Classification, ANN, One Hot Coding

## I. INTRODUCTION

Hospitals are changing their normal methods and replacing them with systemized data to maximize information and communication technology. In the tending sector sensible health will be expected to boost the quality of service at intervals. The emergency unit (ICU) is also a special department at intervals in the health care sector that generally helps folks recover from dangerous injuries and illnesses. Patients at intervals in the intensive care unit need consistent direction from medical employees and caretakers to create a stable health condition.

Early prediction and reliable-prediction tools for some sensitive medical illness or condition will help to solve the medical case and would also be helpful caregiving the aids. Predicting the mortality rate is one of the foremost essential tasks in the essential care analysis. Aim of predicting mortality is not-entirely similar to distinguishing risky folks and to making the correct selections however additionally to saving intensive care unit beds for patients. These results generated by systems are not continually acceptable for each and every patient at intervals in the Intensive Care Unit (ICU) as a result they don't seem to be sufficiently correct. Numerous researches have advances to make correct predictions of mortality rate. The high spatiality will increase the process quality and reduce the model accuracy

## II. LITERATURE SURVEY

Patients with extreme illness who require extensive care are admitted to ICU. Predicting illness early in the treatment is important so that the doctors can treat the patients with great risk and provide immediate treatment and necessary medication based on similar cases data. Patients who have mortality risk higher can be admitted to ICU earlier with the help of early prediction. Such early estimation remains challenging. This model uses ANN to predict the mortality of ICU patients. Our approach is more accurate but Intensive care may be a complex department that always handles cases with different mortality rates, many patients suffer from several diseases simultaneously.

Therefore, patients admitted to the Intensive Care Unit should be monitored 24/7 to avoid Any major fluctuations in patients' health or condition. Intensive monitoring through the Intensive Care Unit equipment leads to large medical records that need efficient and accurate systems for assistance in data analysis. Using Intensive Care Unit data to predict future events, like patient mortality, is taken into account as one of the foremost critical topics in Intensive Care Unit research.

### III. PROPOSED METHODOLOGY

Proposed methodology has 4 major steps – Data-Set Analysis, One Hot Coding, Scaling Data, Building and Fitting ANN

#### A. Data-Set Analysis

One of the key components in any data science project is EDA (Exploratory Data Analysis). This is a process of searching for anomalies(outliers) and patterns in the given data set and also preparing a hypothesis of all the learning.

EDA generates a summary by constructing different graphical representations for the data in the data set which are mostly numerical. This helps us in better understanding the data.

We will be doing this EDA to understand the parameters contributing to mortality rate and neglecting the rest.

	ALP	ALT	AST	Age	Albumin	BUN	Bilirubin	Cholest
ALP	1.000000	0.114850	0.155750	0.000879	-0.137771	0.155416	0.240297	-0.006795
ALT	0.114850	1.000000	0.858741	-0.112012	-0.009850	0.038541	0.109332	-0.024351
AST	0.155750	0.858741	1.000000	-0.088649	-0.037277	0.051244	0.127767	-0.020751
Age	0.000879	-0.112012	-0.088649	1.000000	-0.036231	0.228768	-0.063837	-0.010103
Albumin	-0.137771	-0.009850	-0.037277	-0.036231	1.000000	-0.100987	-0.086068	0.058119
BUN	0.155416	0.038541	0.051244	0.228768	-0.100987	1.000000	0.185473	-0.014453
Bilirubin	0.240297	0.109332	0.127767	-0.063837	-0.086068	0.185473	1.000000	-0.017119
Cholesterol	-0.006795	-0.024351	-0.020751	-0.010103	0.058119	-0.014453	-0.017119	1.000000
Creatinine	0.131899	0.077210	0.092024	0.033369	-0.030867	0.683278	0.140630	-0.024351
DiasABP	-0.035320	0.024430	0.030425	-0.263634	0.077583	-0.119703	-0.031563	0.077210
FiO2	-0.003474	-0.003840	-0.003814	-0.011746	0.001028	-0.009474	-0.004779	-0.296795
GCS	0.020718	-0.073180	-0.123846	0.027736	0.144026	-0.031887	-0.042079	0.010103
Gender	-0.002758	-0.002251	-0.002259	-0.020055	-0.000094	-0.004939	-0.002749	0.000879
Glucose	0.014560	0.049459	0.076040	0.057239	0.030054	0.126179	-0.029639	0.033369
HCO3	-0.095050	-0.088142	-0.117626	0.008126	0.182131	-0.236730	-0.132563	0.020751
HCT	-0.010624	0.047127	0.022552	-0.065288	0.228917	-0.096426	-0.040429	0.077210
HR	0.026164	0.091215	0.104572	-0.246909	-0.137857	-0.060862	0.019632	-0.040429
Height	-0.014689	0.012009	0.016882	-0.088042	0.018550	0.023661	0.012634	0.000879
ICUType	-0.002739	-0.002238	-0.002260	0.021302	-0.000138	-0.004988	-0.002727	0.000879
K	0.018410	-0.004501	0.031697	0.081105	-0.049365	0.264277	-0.020082	0.010103
Lactate	0.047983	0.193083	0.282596	-0.018507	-0.066734	0.037174	0.103735	0.000879
MAP	-0.017456	0.021525	-0.000306	-0.114144	0.091947	-0.080205	-0.032284	0.020751
MechVent	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Mg	0.047530	0.029570	0.042236	0.143433	0.028930	0.299111	0.128935	0.020751
NIDiasABP	-0.011555	0.023721	-0.000169	-0.264847	0.185396	-0.129948	-0.016910	0.020751
NIMAP	-0.031432	0.011535	-0.018653	-0.182128	0.199239	-0.117328	-0.043218	0.010103
NISysABP	-0.041680	-0.006403	-0.031567	-0.003619	0.172102	-0.039398	-0.046814	0.000879
Na	-0.033741	0.021272	0.021510	0.003085	0.031793	0.033020	-0.075726	-0.020751
PaCO2	-0.038665	-0.078684	-0.089867	-0.023488	0.075239	-0.057482	-0.099564	0.010103
PaO2	-0.004341	-0.003155	-0.003046	-0.003788	0.001884	-0.006133	-0.004365	0.000879
Platelets	0.071202	-0.077499	-0.084033	-0.023755	0.019028	-0.034506	-0.146147	0.000879
RecordID	0.013645	0.026546	0.018264	-0.019319	0.019584	-0.033135	-0.022028	-0.171119
RespRate	-0.008747	0.019284	0.014621	0.069773	-0.024060	0.000831	-0.017754	-0.000879
SaO2	-0.024257	-0.067018	-0.095091	0.021496	0.035633	-0.037919	-0.003182	0.000879

Fig. 3.1. Patients Data



### B. One-Hot Coding

We transform the data in one-hot coding to improve the prediction. A binary value of 1 or 0 is given to each categorical column with one-hot coding, which is converted from categorical value. Each integer value is represented by a binary vector  $v$ . The index is designated as 1 and all of the values are zero.

We then plotted a correlation map to understand the features and there relation with other features.

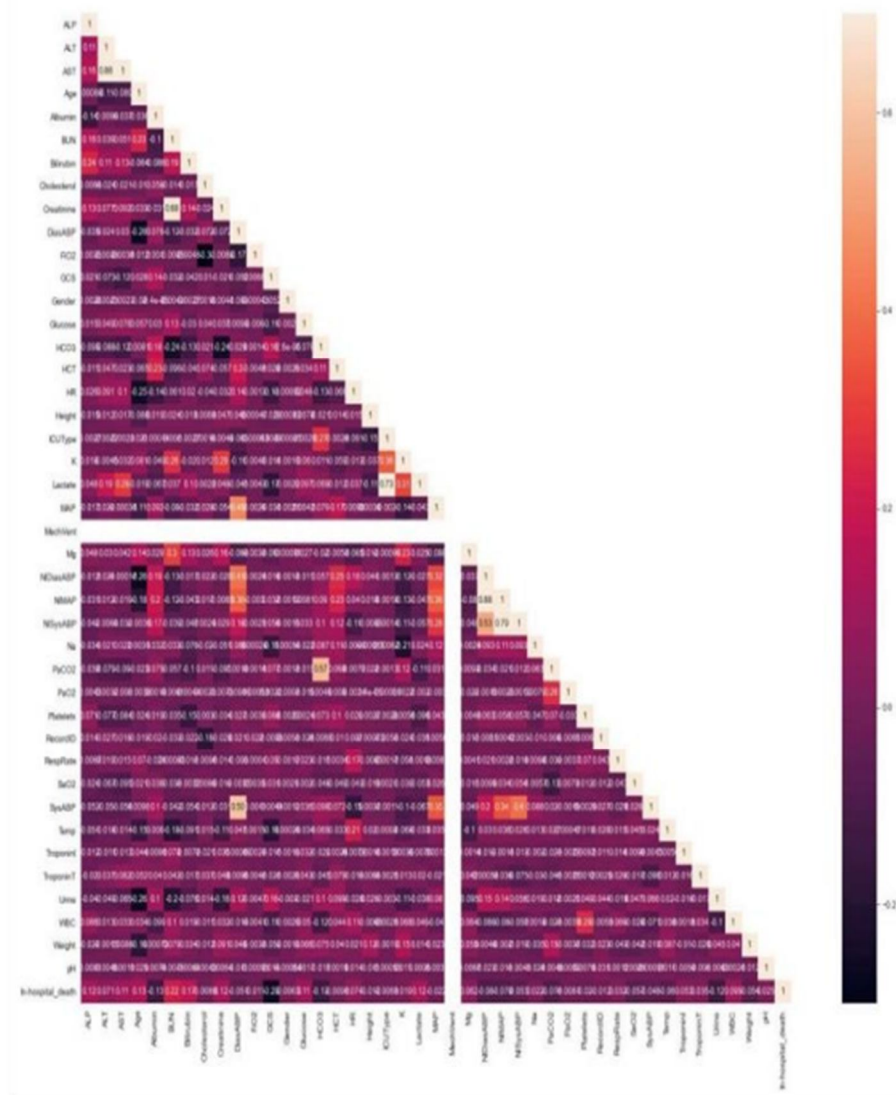


Fig 3.2. Correlational Heatmap

### C. Scaling Data

We scaled the data into a specific range so that it reduces the data. We used MinmaxScaler to scale. Characteristics are scaled to a certain range which changes the form of original distribution.

After scaling the data we split the data set into multiple train and test data sets.

```
print(X_train.shape,X_test.shape,y_train.shape,y_test.shape)
```

```
(3199, 37) (800, 37) (3199, 2) (800, 2)
```

Fig.3.3. Data Sets

#### D. Building and Fitting ANN Model

We build a ANN Model with

- 1) Dense Layers
- 2) Batch Normalization
- 3) Dropout
- 4) Adam Optimizer

##### Building ANN Model

```
[34]: model = Sequential()

model.add(Dense(64, input_dim=X_train.shape[1], activation='relu'))
model.add(Dense(128, activation='relu'))
model.add(Dense(196, activation='relu'))
model.add(Dense(196, activation='relu'))

model.add(BatchNormalization())

model.add(Dense(256, activation='relu'))
model.add(Dense(2, activation='sigmoid'))

model.compile(optimizer = Adam(lr = 0.0005), loss='binary_crossentropy', metrics=['accuracy'])
print(model.summary())
```

Fig. 3.4. ANN MODEL

#### IV. EXPERIMENTATION

We have a dataset which consists of 80% training data and 20% testing data. This model was test against these data. The model is evaluated using

- 1) Accuracy
- 2) Loss
- 3) Confusion Matrix

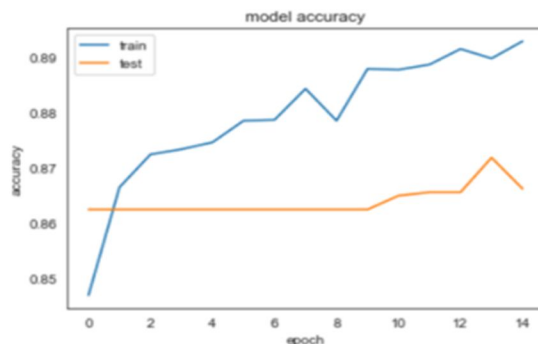


Fig. 4.1 Model Accuracy

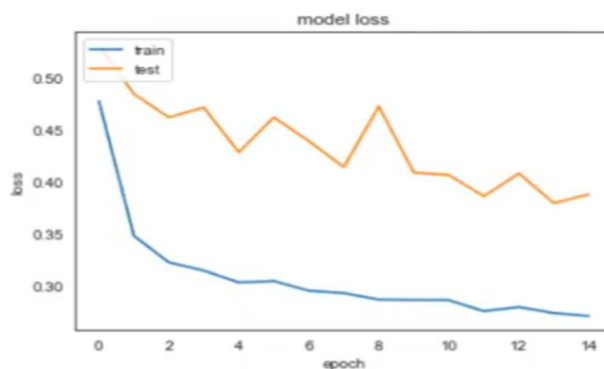


Fig 4.2 Model Loss



## V. CONCLUSION

The above proposed model achieved an accuracy of 87%. This is the highest accuracy it can reach with the given set of data. This model can successfully be used for prediction of mortality in ICU. Still it's a prediction, it can go wrong.

## REFERENCES

- [1] Nora El-Rashidy<sup>1</sup>, Shaker El-Sappagh<sup>2,3</sup>, Tamer Abuhmed<sup>4</sup>, Samir Abdelrazek<sup>5</sup>, And Hazem M. El-Bakry<sup>5</sup>
- [2] Z. Rayan, M. Alfonse, and A. M. Salem, Intensive Care Unit (ICU) Data Analytics Using Machine Learning Techniques, vol. 26, no. 1. Sofia, Bulgaria: ITHEA, 2019, pp. 69–82.
- [3] G. Rouleau, M.-P. Gagnon, and J. Côté, “Impacts of information and communication technologies on nursing care: An overview of systematic reviews (protocol),” Systematic Rev., vol. 4, no. 1, pp. 1–8, Dec. 2015.
- [4] K. M. D. M. Karunaratna, “Predicting ICU death with summarized patient data,” in Proc. IEEE 8th Annu. Comput. Commun. Workshop Conf. (CCWC), Jan. 2018, pp. 238–247.
- [5] R. Sadeghi, T. Banerjee, and W. Romine, “Early hospital mortality prediction using vital signals,” Smart Health, vols. 9–10, pp. 265–274, Dec. 2018.



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