
### Investigation into the Strengths and Limitations of Artificial Neural Networks:
#### An Application to an Adult ICU Patient Database

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The objective was to determine the optimal operating conditions for an artificial neural network (ANN) to estimate outcomes. The simulations involved using the 51 inputs while changing the desired output variable. Comparing the correct classification rate (CCR) of an ANN with that of a constant predictor (CP) results indicates the minimum number of sample patterns an ANN requires for minimally acceptable outcome estimation, and establishes the limitation of the ANN as a useful tool.

#### INTRODUCTION

Few medical researchers have achieved correct classification results with ANNs in the 90+% range [1]. This paper discusses how well a backpropagation feedforward ANN separates two output classes as the representation of the dominant class approaches 100%.

#### METHODOLOGY

We performed the simulations using the same database and neural network code as Trigg [1] with the data sorted into two categories: post-operative and nonpost-operative patients. We used the CCR and average squared error (ASE) to evaluate the performance of the network.

Six different situations involving the number of hours of mechanical ventilation were investigated (≤ 4 hrs, 12, 24, 36 and 336 hrs, and between 24 and 336 hrs), as well as estimates of the length of ICU stay (0, ≤ 1, 4, 5, and 14 days). A commonly estimated medical outcome is mortality (or “survival rate”), therefore, this output variable was also investigated. The objective was to observe the changes in CCR and ASE for each outcome.

#### RESULTS

From the simulation results, it appears that the ANN had more difficulty classifying the NONPOSTOP patients than the POSTOP patient cases. A possible explanation is the extreme diversity of the circumstances surrounding the patients in the NONPOSTOP subdatabase, making them more difficult to classify.

To see the relationship between the CCR of the CP and the ANN for the two databases, we plotted the results of CCR versus the proportion of representative samples in the database. The results showed that the CCR of the ANN and the CP converge to a theoretical limit for the superior performance of the ANN. This occurs as the division between the two desired outputs becomes highly skewed towards 100% for one of the outcomes. In cases where the number of sample patterns for a particular case are quite small, after the first few experiments with the ANN, everything becomes classified as belonging to the largest class — in essence, the ANN becomes a CP.

Using linear regression of the CCR for the ANN, we approximately identified this limit. The point at which the linear regression line crosses the CP predictions would be the theoretical limit for the ANN. After this point, as the division between the output classes becomes more skewed, the ANN either becomes a CP or its CCR is lower than that of a CP. We discovered that the dominant output class may represent at most 85.9% of the POSTOP database, and 83.5% for the NONPOSTOP database under consideration.

#### CONCLUSION

For this adult ICU patient database, it seems that in order to have a notable improvement over a CP, the ANN requires the dominant output class to represent no more than 85.9% of the database for POSTOP patients, or 83.5% of the cases in a NONPOSTOP database. These limitations cannot necessarily be directly applied to other databases (medical or otherwise) because the ANN relies heavily on the relationship between the input parameters. However, this information could be used as a guideline for other applications.

#### References


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