Comparison of Artificial Neural Network Architectures by the Separation Quality of Signals from a Digital Neutron Spectrometer

T. Bobrovsky, P. Prusachenko, V. Khryachkov

Institute for Physics and Power Engineering, Obninsk, Russia

ABSTRACT

Machine learning is one of the popular methods for analyzing and processing complex data. Despite shown good accuracy, Appling it in the scientific field is hindered by the unpredictable neural networks behavior. Thus, incorrect results can be able caused by applying neural networks to separate particles in scintillator. Therefore, it was necessary to compare series different neural networks architectures and to find out the feasibility of their application to the task of separating particles according to the shape of the pulse.

1. INTRODUCTION

Mostly, gamma radiation goes with neutron radiation. For this reason, ability of most organic scintillators to separate signals by pulse shape is very important. At nowadays, to separate the signals by pulse shape uses both digital and analog methods. At the same time, there is the possibility of using artificial neural networks (ANN). A number of studies have shown good results of using ANNs to solve this problem [1–3, 5–6]. However, in the most works published on this topic, there are no sound estimates of the quality of the separation of signals in relation light output. Comparison of different architectures has not done.

The purpose of this work was to train several types of ANNs, to obtain a reasonable estimate of the recoil protons false count rate and the efficiency of registration of recoil protons.

2. MATERIALS AND METHODS

In this work, we had used early-obtained in [6] data. In [6] neutrons spectrum of ^{252}Cf spontaneous fission was measured by using time-of-flight method. To detect neutrons we used crystal stilbene with size 2×2 cm. This scintillator was paired with PMT EQ Enterprise 9813 QB. An offset voltage of 1150 V was applied to it. Thin ^{252}Cf layer was placed on flat parallel ionizing chamber cathode. Chamber inter electrode gap was 2 mm. Signals form ionizing chamber gained in charge sensitive amplifier. PMT signals and chamber signals digitized with Ultraview AD14-500MHz and wrote together. Last dynode was source of trigger signal accumulated about 3.8 million events.

Supervised learning is main method to train ANN. In a few words, ANN takes sample of data and configures inherent state to produce required data, for example, event class. For this training method is necessary to obtain training data set which, in our case, represented as labeling signals set. Signals labeling was performed by correlation analysis [6]. The separation parameter R is determined from eq.1:

$$R = \frac{Max(\sum_{j=-inf}^{inf} f_j * g_{i-j})}{A}, \tag{1}$$

where A – signal area, *f* – analyzed signal, *g* – averaged electron signal.

For low light-output region separation curve was calculated by rule that false recoil protons number was less than 1%. For higher energy region, separation curve was passed through the intersection point of the particles distributions. The signals had length of 200 channels. Label “0” corresponded to recoil protons, “1” – electrons. Each signal was normalized to the maximum amplitude. Besides, for MICNN were calculated three additional signals: smoothed, differentiated, cumulative sum for each sample.

Table 1. Train set composition.

Energy window, keVee	Recoil protons	Electrons
45 – 124	1000	1000
124 – 520	1000	1000
520 – 915	500	500
915 – 1311	500	500

ANNs was performed by using the Python libraries Keras and Tensorflow [5, 9]. The following neural networks (fig.1) were investigated: single-layer perceptron (Per), multilayer perceptron (MLP), convolutional neural network (CNN), multi-input convolutional neural network (MICNN) [10], recurrent neural network (RNN). All layers in ANNs had activation function “ReLU”, besides LSTM [4] layer and output layer. Output layer of each ANN have sigmoid activation function. To avoid overfitting was used random weight zeroing (Dropout). Adam (adaptive moment estimation) optimizer we used to train ANNs. The loss function was mean squared error.

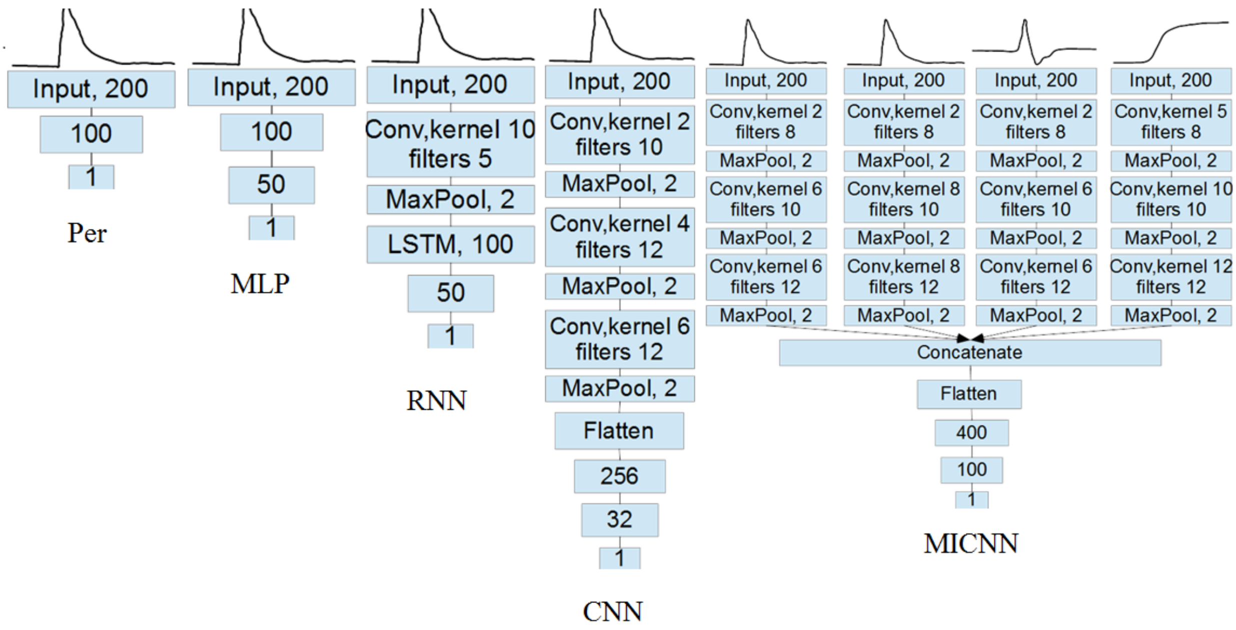

Figure 1. ANNs architectures.

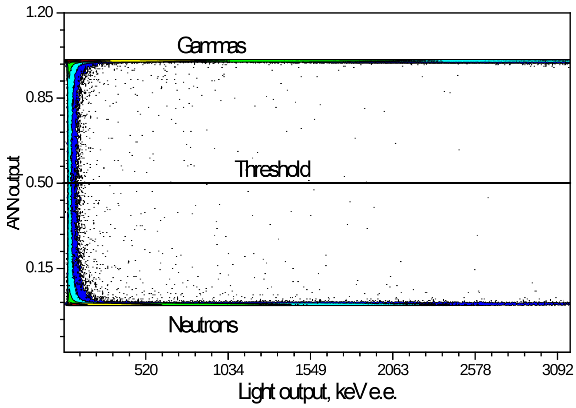

Figure 2. Example of two-dimensional spectra for MICNN.

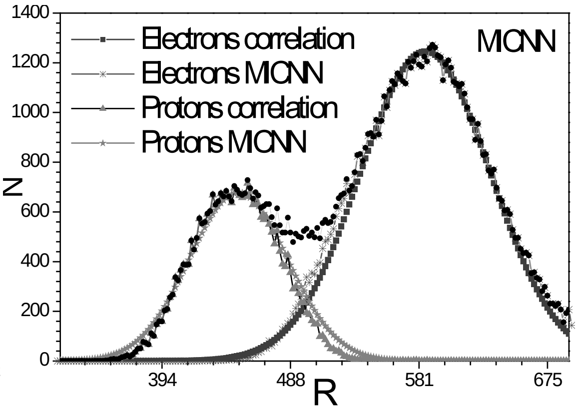

Figure 3. Correlation analysis for separated by MICNN particles at 45 keVee.

2.1 Separation quality

To calculate false count rate of recoil protons (Fig. 4) were used “clear” signals from electrons obtained using information about time-of-flight. The proportion of background neutrons in the instant gamma peak was about $4.5\cdot10^{-5}$.

False count rate is:

$$f = \frac{N_{FP}}{N_{TE}+N_{FP}}, \tag{2}$$

N_{FP} – number of false identify protons, N_{TE} – number of true identify electrons.

Registration error of recoil protons was founded by eq. 3:

$$e = \frac{(A_{p.\,ap}-(A_{p.NN}-f*A_{e.\,ap}))}{A_{p.\,ap}}, \tag{3}$$

f – false count rate of recoil protons, $A_{p.ap}$ – number of recoil protons obtained from approximation of cuts two-dimensional spectrum for correlation analysis, $A_{e.ap}$ – number of electrons obtained from approximation of cuts two-dimensional spectrum for correlation analysis, $A_{p.NN}$ – number of recoil protons obtained by ANN.

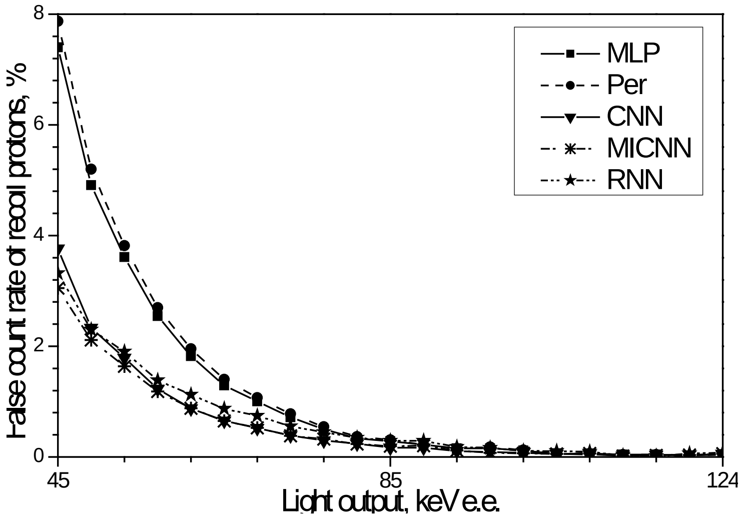

Figure 4. False count rate for ANNs.

All neural networks have similar values of false protons count rate and lost protons above 85 keVee (Figs. 4, 5). However, in low energy range the situation is changing. Complicated neural networks much less fault in definition particle type according to simple neural networks that mostly used in the earlier studies. At the same time registration efficiency of neutrons for complicated neural networks worse than for simple neural networks.

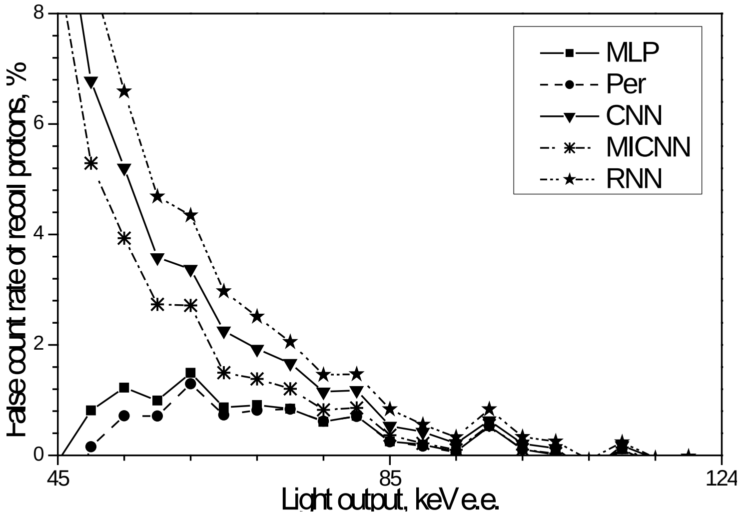

Figure 5. Proportion of lost recoil protons.

2.3 Performance

Processing speed was measured for kernels of each algorithm. For neural network was measured time for front propagation, CI – integrals calculation, correlation analysis – parameter R (eq.1) calculation. The test was carried out on PC that had the following characteristic: four-threaded Intel core i3-3220 3.3 GHz processor, DDR3 4 GB RAM, windows 7x64.

Table 2. Processing time for 1000 samples.

Algorithm	**time, ms**
Correlation analysis	37.8
Charge integration	1.3
Per	3.9
MLP	6.6
CNN	65.5
MICNN	181.7
RNN	374.8

CONCLUSION

A reasonable estimate of the false identification of neutrons by neural networks has been obtained. Was compared the several neural network architectures. The comparison was made of the operation speed of some standard digital algorithms for separating signals according to the pulse shape and the presented artificial neural networks. By the level of false classification, convolutional neural networks showed better results, but the calculations take longer than classical methods.

REFERENCES

1. Doucet E. et al., NIM A, available online 24 Sep. 2018.
2. Fu C. and all. Annals of Nuclear Energy, Volume **120** (2018) 410–421.
3. Griffiths J. et al., physics.ins-det, 19 July 2018.
4. Hochreiter Sepp and all. Neural Computation **9**(8), (1997) 1735–1780.
5. Keras: The Python Deep Learning library.
6. P.S. Prusachenko et al., NIM A, Volume **905** (2018) 160–170.
7. Söderstörm P.-A. et al., NIM A, Volume **916** (2019) 238–245.
8. Tambouratzis T. et al., JAISCR. December 2014.
9. Tensorflow. An end-to-end open source machine learning platform.
10. Zhicheng Cui et al., cs.CV, 22 Mar 2016.