Corrigendum: Application of Convolutional Neural Networks in Neutrino Physics (2021) Journal of Physics: Conference Series (JPCS). Vol. 1730, Article number: 012116 (doi:10.1088/1742-6596/1730/1/012116)

Adam Novotný, Jiří Franc
Department of Mathematics, Faculty of Nuclear Sciences and Physical Engineering, Czech Technical University in Prague, Czech Republic

Page 1:
In the Abstract section, the following text appears:

“These visual images are tailored to fit measured data from future Deep Underground Neutrino Experiment.”

This should read:

“These visual images are tailored to fit measured data from neutrino experiments.”

Page 2:
In the Introduction section 1, the following text appears:

“Figure 1. Electron neutrino \( \nu_e \) event from three views.”

This should read:

“Figure 1. Electron neutrino \( \nu_e \) event in MC prediction from three views ([1])”

Page 2:
In the Classification overview section 2, the following text appears:

“Figure 2. SE-ResNET34 architecture.”

This should read:

“Figure 2. SE-ResNET34 architecture (figure reproduced from [2]).”

Page 4:
In the 4.1 Acknowledgments section, the following text appears:

“4.1. Acknowledgments
These results were supported by the research grants SGS18/188/OHK4/3T/14 (MEYS), LTT180001, LM2015068, and CAAS EF16 019/0000778 (MEYS/EU).”
This should read:

“4.1. Disclaimer and Acknowledgments
This work is intended as a student investigation into statistical analysis, is based on the work described in DUNE’s CVN paper [2], and is not intended to address DUNE classification capabilities.
These results were supported by the research grants SGS18/188/OHK4/3T/14 (MEYS), LTT180001, LM2015068, and CAAS EF16 019/0000778 (MEYS/EU).”

Page 4:
In the References section, the following text appears:

“[1] Acero MA, et al. 2018 New constraints on oscillation parameters from nu_e appearance and nu_mu disappearance in the NOvA experiment Physical Review D 98 (3)
[2] Acero MA, et al. 2019 First measurement of neutrino oscillation parameters using neutrinos and antineutrinos by NOvA Physical Review Letters 123 (15) ”

This should read:

“[1] Abi B, et al. 2020 Far detector technical design report (DUNE Collaboration), Volume II: DUNE physics, Report No. FERMILAB-PUB-20-025-ND, https://arxiv.org/abs/2002.03005
[2] Abi B, et al. 2020 Neutrino interaction classification with a convolutional neural network in the DUNE far detector Physical Review D 102 (9) ”

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Application of Convolutional Neural Networks in Neutrino Physics

Adam Novotný, Jiří Franc
Department of Mathematics, Faculty of Nuclear Sciences and Physical Engineering, Czech Technical University in Prague, Czech Republic
E-mail: novotad2@fjfi.cvut.cz, jiri.franc@fjfi.cvut.cz

Abstract. Convolutional neural networks (CNNs), as a deep learning algorithm, have successfully been used for analyzing visual image data over the past years. As some of the physical experiments can produce image-like data, it is more than fitting to combine the interdisciplinary knowledge between high energy physics and deep learning. Especially in the domain of neutrino physics, the particle classification problem has played an important role and CNNs have shown exceptional results for the image classification. In this paper, results of application of CNN called SE-ResNET on Monte Carlo simulated image data is presented. These visual images are tailored to fit measured data from future Deep Underground Neutrino Experiment. The image classification focuses primarily on neutrino flavor classification, namely on classification of charged current (CC) electron $\nu_e$, CC muon $\nu_\mu$, CC tauon $\nu_\tau$ and neutral current (NC); and secondarily on other characteristics of the image, such as whether the observed particle is neutrino or antineutrino. The results are important for further physical analysis of the neutrino experiment event, e.g. for study of neutrino oscillation.

1. Introduction
Statistical data analysis has grown to play a very important role in many fields of study and high energy physics (HEP) does not stay behind. Neutrino physics, as its subset, is concerned with exploration of various properties of neutrino particle (denoted by $\nu$). At the moment, three distinct groups of $\nu$ are being explored, which are called flavors. These are electron $\nu_e$, muon $\nu_\mu$ and tauon $\nu_\tau$ neutrino.

A plethora of procedures need to be performed in order to discover the yet unknown knowledge about neutrinos. One of the core problems is the correct categorization of the particles recorded in the detectors [1, 2]. In case of some neutrino experiments, neutrino event is reconstructed as a visual image, see Fig. 1. If needed, such HEP data can be pre-processed by various statistical methods before classification procedure is carried out (e.g. [3]). For this cause, deep learning methods have proved successful. Discoveries in the field of deep learning, which is concerned with artificial neural networks and their modifications, have enabled a new approach towards particle classification. Concretely, convolutional neural networks applied on visual image data provide a significant improvement of classification results and outperform past algorithms.

In this paper, we primarily present the results of neutrino particle classification from Monte Carlo Challenge 9 simulated image data, which are generated to fit future measured data from Deep Underground Neutrino Experiment. Secondly, we present classification of six additional variables of a neutrino event.
2. Classification overview

The Monte Carlo dataset consists of approximately 3 million image-like samples. Each sample is a three-view image with a resolution of 500 times 500 pixels and a corresponding label. Samples are labeled in four flavor classes, two neutrino-antineutrino classes, four interaction classes and four classes each of overall number of protons, pions, pizeros and neutrons.

Concretely, the dataset includes 4 neutrinos flavors: CC $\nu_e$, CC $\nu_\mu$, CC $\nu_\tau$, NC; antineutrino $\bar{\nu}$ and neutrino $\nu$; 4 interaction types: CC quasi-elastic scattering (CC QE), CC resonance production (CC RES), CC deep-inelastic scattering (CC DIS), CC (CC Other); number of protons $p$: 0, 1, 2, > 2; number of pions $\pi$: 0, 1, 2, > 2; number of pizeros $\pi^0$: 0, 1, 2, > 2; number of neutrons $n^0$: 0, 1, 2, > 2.

The dataset is further split into training, validation and testing set; resulting in 3,212,351 total images split into training 3,148,073 (∼ 98 %) images, validation 32,290 (∼ 1 %) images and testing 31,988 (∼ 1 %) images.

Convolutional neural network used for classification is called SE-ResNET34 (Squeeze-and-excitation residual neural network with 34 convolution layers) with three initial branches and seven output layers. We use the architecture in two settings; firstly having one flavor output layer; secondly having seven output layers. The architecture diagram is shown in the Fig. 2.
For training of the CNN, binary cross-entropy loss function is used for binary classification and categorical cross-entropy loss function is used for multiclass classification. Concerning hyperparameters, stochastic gradient descent with Nesterov momentum (with value of 0.9), starting learning rate (0.1 decreasing over epochs) and He weight initialization and weight decay (0.0001) are used. As the dataset is already quite large, dataset augmentation is not used. Missing labels are masked during training. Samples are reshuffled after each epoch so training is more generalized. The overall number of training epochs is 15, the most optimal model is later chosen based on flavor accuracy.

All of the mentioned was implemented in Python 3.6.6 within the Tensorflow 1.13.1 framework, deployed on GPUs platform, and Keras 2.3.1 on top of Tensorflow. The computations were deployed on four NVIDIA Tesla V100.

3. Classification results
As mentioned, we use the CNN architecture in two settings, classifying only flavor in the first place and classifying six additional (seven overall) variables in the second. Therefore, the multiclass flavor classification and multiple multiclass classification are conducted.

To obtain better understanding of data structure and distribution, statistical estimates or tests by means of appropriately selected metric were performed [4, 5].

The test accuracy and receiver operating curve (ROC) with corresponding area under curve (AUC) is presented, calculated in one-vs-all fashion. A line representing random guess is additionally drawn. Other additional metrics, both during training and testing phase, are omitted in this paper.

3.1. Flavor classification
The final test flavor accuracy is 0.778, ROC and AUC can be seen in the Fig. 3. The main focus is on $\nu_e$ and $\nu_\mu$, which yield the best results.

![Receiver operating characteristics: Flavor](image)

**Figure 3.** ROC and AUC of the flavor classification.

3.2. Multiple classifications
The final test accuracy for subsequently flavor, neutrino/antineutrino property, interaction, number of protons, pions, pizeros and neutrons are 0.778, 0.846, 0.619, 0.526, 0.607, 0.762, 0.990. The resulting ROCs and AUCs can be seen in 4.

4. Conclusion
Statistical classification of neutrino flavor of image-like data from Monte Carlo Challenge 9 was presented. In addition to the flavor classification, classification of interaction, number of protons, pions, pizeros, neutrons and whether the observed particle is neutrino or antineutrino, was also presented. The metrics of the resulting model was later shown, namely accuracy, receiver
Figure 4. Receiver operating curves of 6 remaining variables.

operating curve and area under this curve. All mentioned enables future physical analysis of the neutrino experiment event.

4.1. Acknowledgments
These results were supported by the research grants SGS18/188/0HK4/3T/14 (MEYS), LTT180001, LM2015068, and CAAS EF16 019/0000778 (MEYS/EU).

References
[1] Acero MA, et al. 2018 New constraints on oscillation parameters from $\nu_e$ appearance and $\nu_\mu$ disappearance in the NOvA experiment Physical Review D 98 (3)
[2] Acero MA, et al. 2019 First measurement of neutrino oscillation parameters using neutrinos and antineutrinos by NOvA Physical Review Letters 123 (15)
[3] Kus V., Finger R 2019 Unifying approach to score based statistical inference in physical sciences Journal of Physics Conference Series 1391 (1), 012124
[4] Hrabáková J, Kus V 2013 The Consistency and Robustness of Modified Cramer-Von Mises and Kolmogorov-Cramer Estimators Communication in Statistics-Theory and Method 42 (20), 3665-3677
[5] Hrabáková J, Kus V 2017 Notes on consistency of some minimum distance estimators with simulation results Metrika 80 (2), 243-257