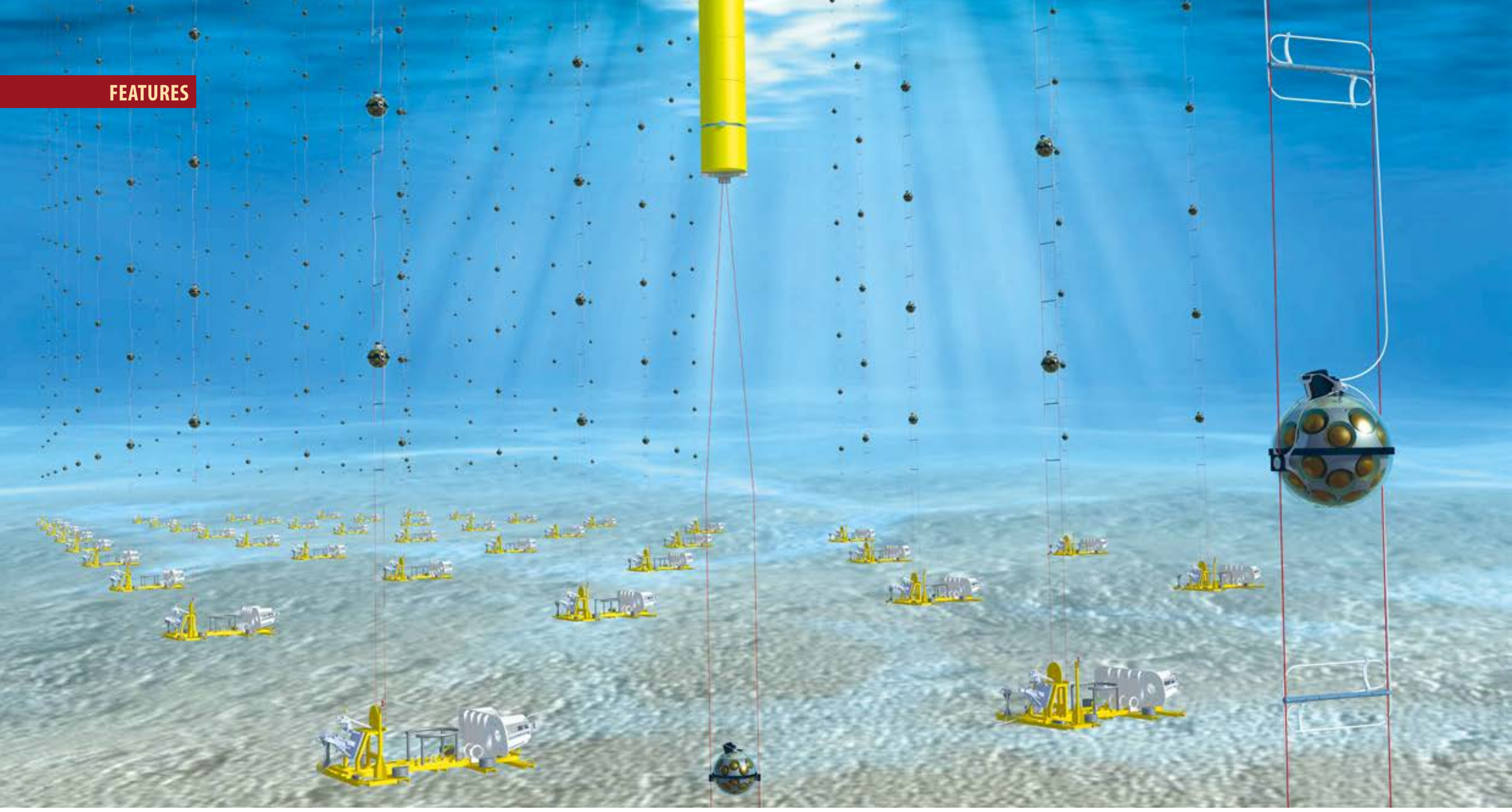

MACHINE LEARNING TECHNIQUES DEEP UNDERWATER IN KM3NET

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Deep in the water of the Mediterranean Sea, the KM3NeT detectors aim at the exploration of the cosmos through the detection of neutrinos and to determine the neutrino mass ordering. Machine learning techniques are widely used to push the performance of the detectors to the limit.

▲ FIG. 1: Rendition of a KM3NeT detector anchored to the seabed. In reality daylight does not reach the depths at which the detectors are installed. Credit KM3NeT Collaboration

The deepest abysses of the seas do not simply represent the last frontier of exploration of our planet. They also give an opportunity to look at the farthest reaches of the cosmos. With the two detectors ARCA and ORCA[1] well under construction in the Mediterranean Sea, KM3NeT has the ambitious goal to detect neutrinos coming from astrophysical sources such as supernovae, gamma ray bursters or colliding stars; and to study neutrino properties exploiting neutrinos generated in interactions of cosmic rays in the Earth's atmosphere [1].

The detectors of KM3NeT

ARCA and ORCA, respectively tailored to the two main scientific aims of KM3NeT, are built as grids of optical sensors which can detect the faint light signals induced by the Cherenkov effect when the secondary particles produced in neutrino interactions propagate in the water of the deep sea. A rendition of the detector grid is shown in Fig. 1. The ARCA detector is located at about 90 km from the coast of Capo Passero, at the southern tip of Sicily, at a depth of almost 3500 m. ORCA is located about 40 km offshore Toulon, not far from the installation site of the predecessor experiment ANTARES[2] [2], at a depth of about 2500 m.

The technology of KM3NeT has been developed building to a large extent on the experience achieved with ANTARES. The basic detection node of KM3NeT

[1] ARCA/ORCA: Astroparticle / Oscillation Research with Cosmics in the Abyss
[2] ANTARES: Astronomy with a Neutrino Telescope and Abyss environmental RESearch

is represented by the optical module (Fig. 2), a pressure-resistant glass sphere equipped with 31 photomultipliers with a three-inch photocathode diameter. The module also includes timing and positioning calibration devices and the electronics for data acquisition and long-range communication [3]. Eighteen modules are arranged on a vertical detection unit which stands on the sea bottom to a height of almost 700 m in ARCA and 200 m in ORCA. The detection units have a slender design (see Fig. 1): the optical modules are attached to two ropes stretching from an anchor resting on the sea floor to a top submersed buoy meant to keep the structure taut. An electro-optical backbone cable runs the full length of the unit and connects all optical modules to an interface module located on the anchor, which is in turn connected through a network of submarine cables and junction boxes to a control station located onshore. For installation purposes, the detection unit is mounted on a launcher vehicle [4] which is temporarily attached to the anchor (Fig. 3); once this compact stack has been deployed to the predefined position on the sea floor, and the connection to the submarine network has been made, a release mechanism is opened by a remotely operated vehicle, leaving the buoyant launcher vehicle free to rise and float to the sea surface, while the detection unit unfurls from it. In their full configurations, ARCA will comprise a forest of 200 such detection units, ORCA more than 100. At the current stage of construction, data taking is already taking place using a total of 18 detection units which have been installed in the two sites.

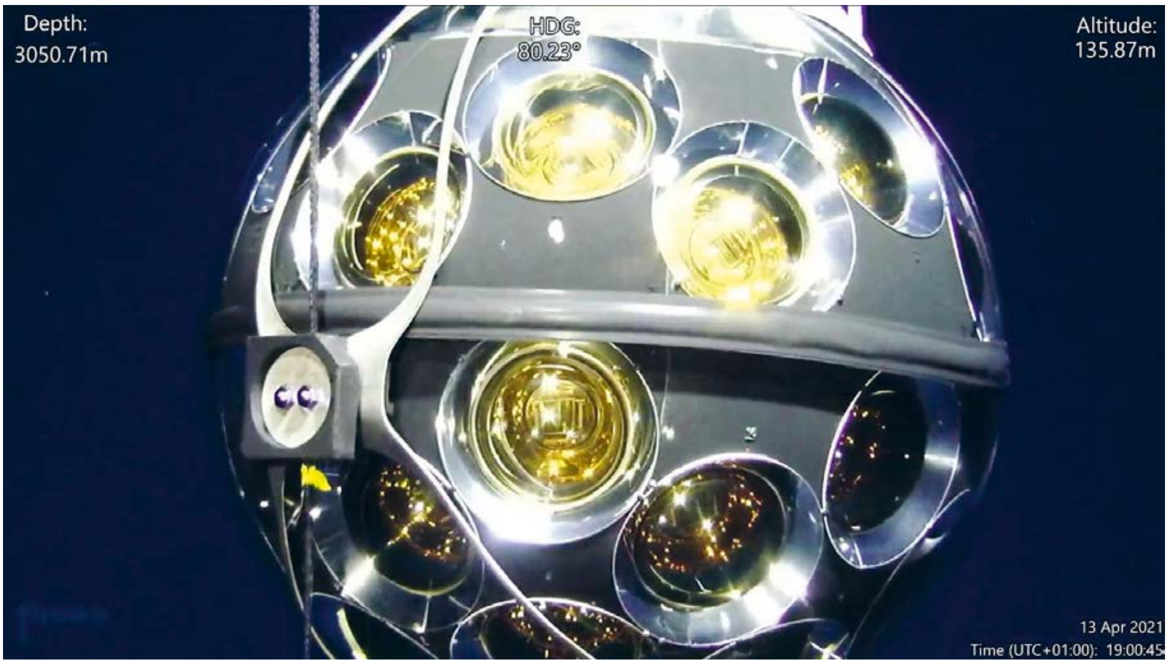
Machine learning techniques

The photomultiplier signals - 'hits' - are used to reconstruct the properties of the incoming particles, such as their energy and direction. For this purpose, the nanosecond-precision arrival time of the light at the sensors, the position of the sensors, their orientation, and the amount of light registered by each photosensor are recorded in a time window defined around the decision of one or more trigger algorithms. The hits recorded in such an 'event' then serve as input for offline reconstruction and classification algorithms.

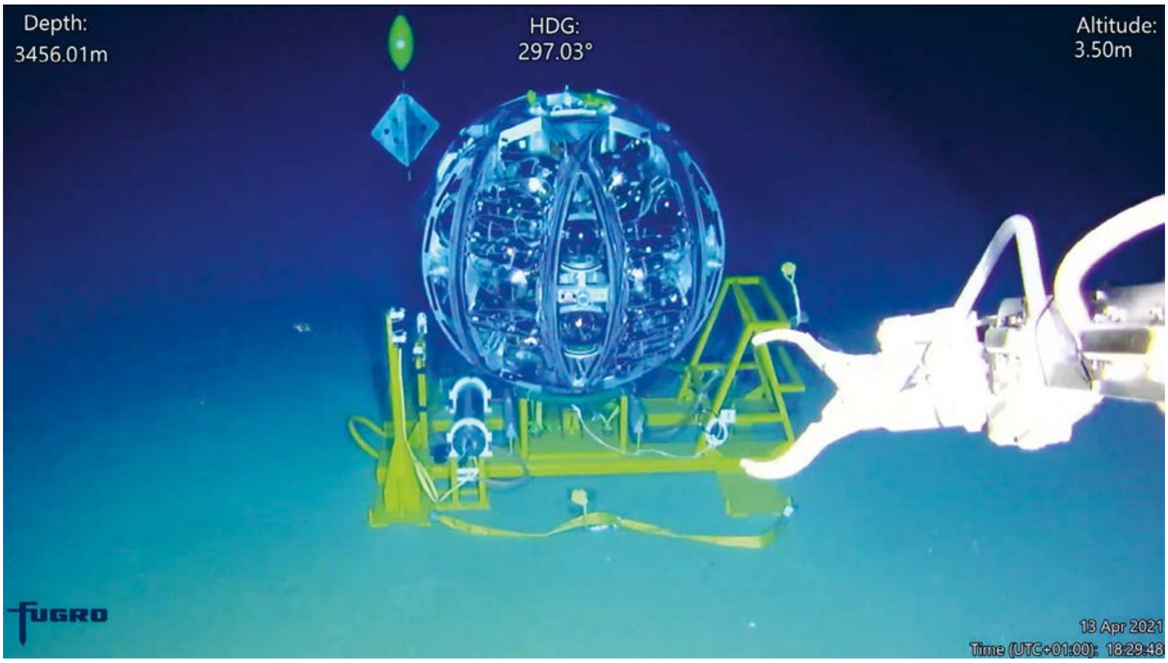
KM3NeT can detect all possible configurations of neutrino-induced events, including long tracks due to high-energy muons, multi-muon events, and the more complex signals due to electromagnetic showers and the hadronic cascades of secondary particles induced in neutrino-nucleus interactions. Classical machine learning techniques for the offline analysis of KM3NeT data have been in use since the start of the project. KM3NeT mainly employs algorithms based on sets of decision trees for event-type classification that are trained on extensive sets of Monte-Carlo simulations. Random decision forests, an ensemble learning method for classification, has been applied successfully to the identification of atmospheric muon events, which may provide million times more abundant detectable events than neutrinos and represent the main background to neutrino event identification in a neutrino telescope. With this technique, it could be shown that an efficient background suppression is possible. The method is also applied for the identification of different neutrino flavours and interaction types. For this purpose, the spatial and temporal distribution of the hits is used to calculate discriminating observables that encode information about flavour and interaction type.

Performance

Recently, the use of random decision forests in KM3NeT has been superseded by another predictive model that also uses ensembles of weak learners to build a ●●●



◂ **FIG. 2:** A photo of an optical module in the deep sea at a depth of 3050 m. Credits KM3NeT Collaboration.

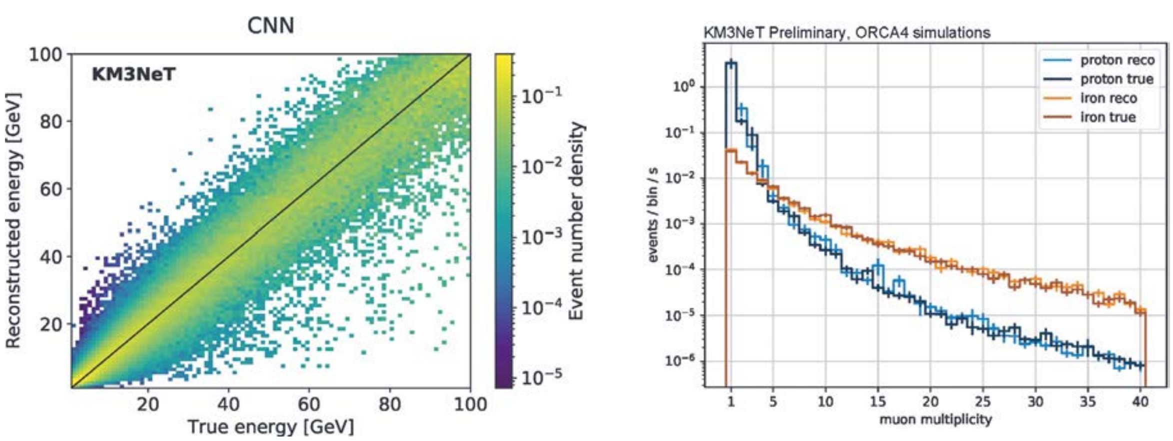


▶ **FIG. 3:** Detection unit in its launcher vehicle, anchored to the seabed at 3456 m. in the foreground the arm of the submarine which will activate the release mechanism for unfurling. Credits KM3NeT Collaboration.

••• strong classifier, XGBoost [5], an open-source software library well known for winning various awards, notably the HiggsML challenge. It has been found to outperform random decision forests while integrating more easily, in particular for machine learning applications, into the KM3NeT software eco system, which is largely based on python.

Deep learning algorithms have been adopted in KM3NeT since the middle of the last decade. Convolutional Neural Networks (CNNs), based on their TensorFlow[3] implementation, were explored first and successfully for event classification and neutrino property regression tasks in ORCA [6]. For training and validation of the CNNs, simulated events were transformed into multi-dimensional images binned in space and time. Different CNN architectures have then been tested and trained to achieve the same classification tasks as with the classical machine learning methods, and in addition were used to reconstruct the neutrino direction and energy (see Figure 4 left for an illustration) including a prediction for the respective uncertainty, allowing for resolution binning in data analysis. Based on extensive and detailed Monte-Carlo simulations of the neutrino interactions, the secondary particle propagation and detector response, it has been found that CNNs can outperform the classical decision tree methods for KM3NeT. In order to facilitate the time-consuming training and evaluation process of neural networks for KM3NeT and other neutrino telescopes a publicly available training organiser framework has been implemented [7].

In order to avoid the need for spatial and temporal binning that in general results in a loss of information, and since the data recorded by KM3NeT closely resembles point clouds, Graph Neural Networks (GNNs) have recently been found to be a natural choice for the network architecture. In the input to the GNN, the information of each single hit becomes a network node feature. The architecture of the GNNs used now for KM3NeT closely resembles the ParticleNet model [8]. It comprises three



▶ **FIG. 4:** Left: Energy as reconstructed by a convolutional neural network versus true Monte-Carlo neutrino energy for electron neutrino charged-current events in KM3NeT/ORCA (taken from [6]). Right: GNN reconstructed and true Monte-Carlo muon multiplicity rates in KM3NeT/ORCA with 4 detection units for protons and iron nuclei as cosmic ray primaries.

[1] http://tensorflow.org

edge convolutional blocks, followed by a global pooling layer and two fully connected layers, implemented as an open-source python package based on TensorFlow [8].

The GNN implementation is currently employed for a variety of different networks and tasks. It shows for the same tasks similar or better performance than the previously used CNNs. Consequently, the GNNs are now evaluated and used for neutrino flavour oscillation analyses with ORCA data. Another GNN with a different architecture even allows for the reconstruction of the properties of atmospheric muon bundles. These are created in collisions of cosmic-ray particles with atomic nuclei in the atmosphere. Reconstructing the bundle multiplicity and extension is challenging, and the application opens up the possibility, as illustrated in Fig. 4 right, to study the mass composition of primary cosmic rays exploiting the large data sets of atmospheric muon events collected routinely by very large neutrino telescopes operating in natural media. ■

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