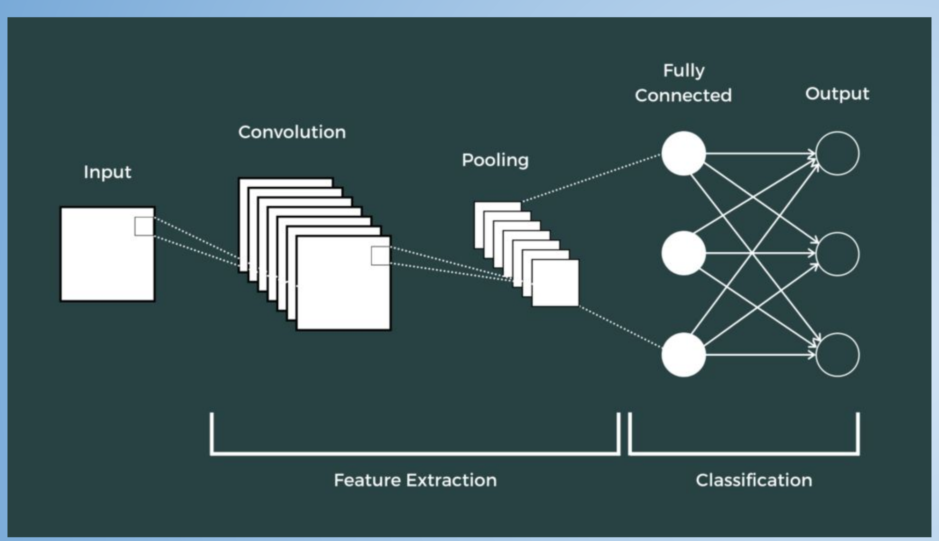
A new Neural Network architecture for Time Series Classification

S. Incardona[1,2*], G. Tripodo[1,2], M. Buscemi[1,2], M. Pourmohammad Shahvar[1,2] and G. Marsella[1,2]
[1] Dipartimento di Fisica e Chimica "E. Segre", Università degli studi di Palermo, Viale delle Scienze, 90128, Palermo, Italy
[2] INFN sezione di Catania, 95123, Catania, Italy
* simone.incardona@unipa.it

Abstract

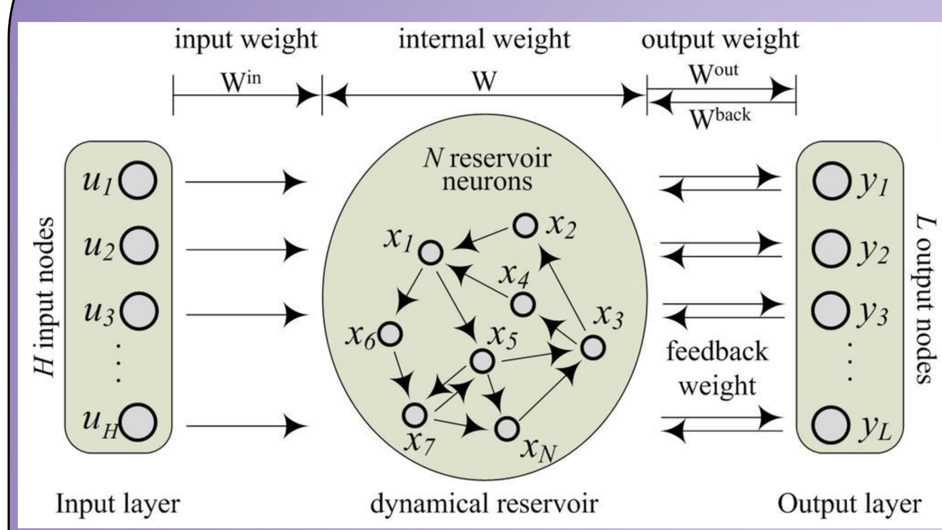
Time Series Classification (TSC) is an important and challenging problem for many subject-matter domains and applications. It consists in assigning a class to a specific time series, recorded from sensors or live observations over time. TSC finds application in different fields, such as finance, medicine, robotics and physics, and it can be used mainly for: Failure prediction, Anomaly detection, Pattern recognition and Alert generation. Several algorithms are designed to carry out time series classification and, depending on the data, one type might produce more accurate compared to the other types. Over the last few years, with the advent of Machine Learning and AI, a lot of algorithms have been developed using, for instance, the Neural Networks, to perform this task. Here we present a new Neural Networks architecture, called Convolutional Echo State Network (CESN), to detect patterns and classify the univariate and multivariate time series. This architecture results from the combination of the Convolutional Neural Networks (CNNs) and the Echo State Networks (ESNs). CNNs are typically used to detect patterns in images and videos, while ESNs are used mainly for forecasting time series from their history. CESN results are declared to be appropriate for the TSC tasks, both univariate and multivariate TS, while demonstrating a higher accuracy and sensitivity compared to previous tests with other existing algorithms. We applied this technique to a simulated data set based on the accelerometers and the gyroscopes to detect falling condition.

Convolutional Neural Networks - CNNs



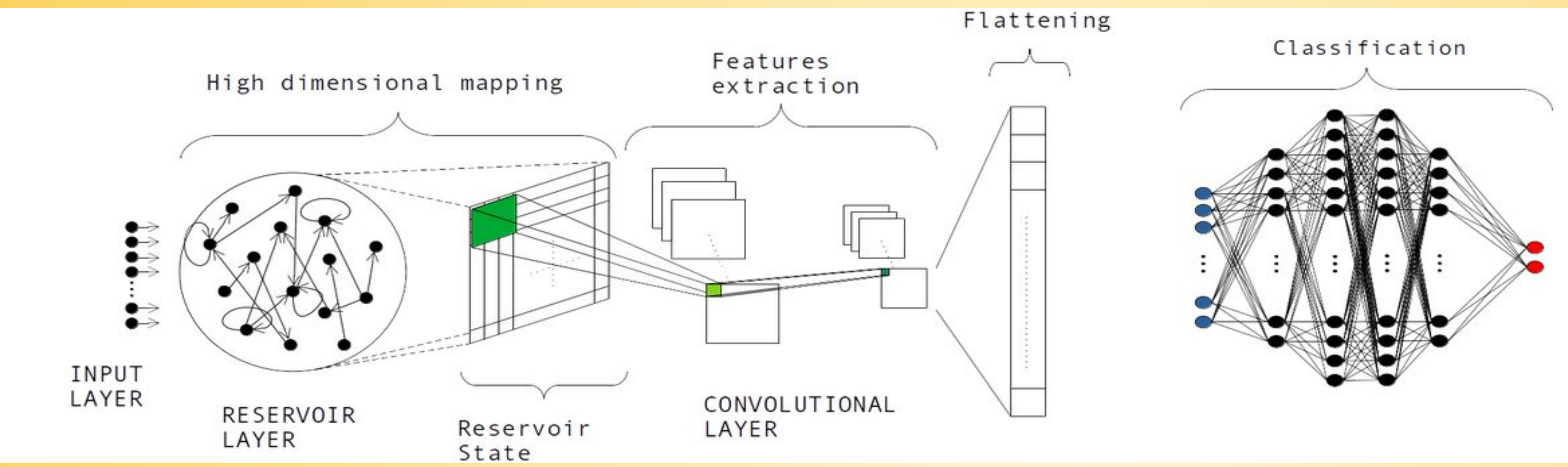
CNNs [1] are a class of Artificial Neural Networks (ANNs) inspired by the animal visual cortex and used for image recognition and processing. These networks include an input layer, a convolutional layer, used to convolve the inputs and pass the results to the next level, a pooling layer, which reduces the dimension of data, and a fully connected layers that are used for the classification part. These NNs are suitable to detect spatial patterns inside the data and these are typically used for image and video recognition.

Echo State Networks - ESNs



ESNs [2] are a type of Reservoir Computing (RC) that use a Recurrent Neural Network, called Reservoir, for the detection of temporal and nonlinear patterns of a time series. These networks are typically used for the forecasting of time series starting from their histories. Their peculiarity lies in the fact that, differently from others RNNs, such as the Long Short-Term Memory (LSTM), the only weights that are modified during training are the output weights which connect the reservoir with the output layer. This allows reducing drastically the computing power and the training time.

Convolutional Echo State Network - CESN



In this section, we present a new NN architecture for time series classification, *CESN*, developed exploiting the great power of CNNs to detect spatial features and the ability of ESNs to detect non linear and temporal patterns. This is shown in the figure on the left and it presents the following layers:

- **Input Layer**
- **Reservoir Layer**
- **Convolutional Layer**
- **Fully Connected Layer - FCL**

Reservoir layer allows to project into an high dimensional space data coming from the input, while the convolutional layer is able to detect patterns generated from the previous one. FCL allows to classify features extracted from the convolutional layer. To test this architecture three different datasets are used. The first one is the so called *"SisFall"* dataset [3], which consists of falls and activities of daily living (ADL) recorded by a device that incorporates an accelerometer and a gyroscope. This data was recorded from people with different age and different sizes and consist of multivariate time series with a fixed length. In order to generalize CESN to time series classification we also used other two dataset: *"ECG200"* and *"ECG5000"* [4]. These consist of series that track the electrical activity recorded during one heartbeat. In particular, for ECG200 the number of classes is two and they are a normal heartbeat and a Myocardial Infarction, while in the ECG5000 the number of classes is five.

Evaluation & Results

Before feeding the network, the pre-processing phase to check the missing values, noisy data, and other inconsistencies, such as different length of the time series, is implemented. This new approach to time series classification by using CESN has allowed achieving similar accuracies and sometimes compared better to other algorithms, both classical and neural. In the figure below (left) we can see the trend of the model accuracy and the model loss, both for training data and validation data. To check the performance of CESN, we use different metrics which are typically used in this context, such as Accuracy, Sensitivity, Specificity and F1-score. By using these metrics, we are able to demonstrate the supremacy of this new architecture over a wide range of algorithms that usually are used to solve this task. Figure below (right) exhibits the confusion matrix of the ECG200 dataset. This can be seen as a representation of the correct classification of any algorithm used for this task.

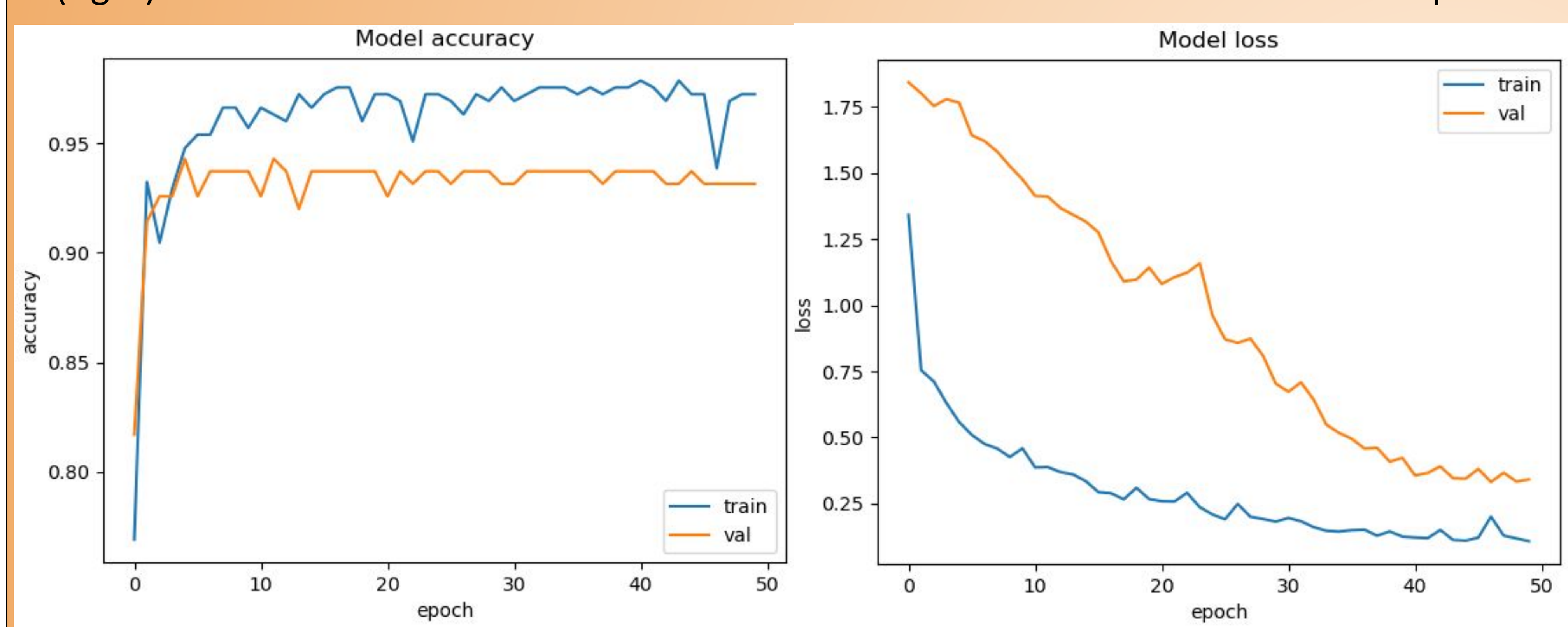
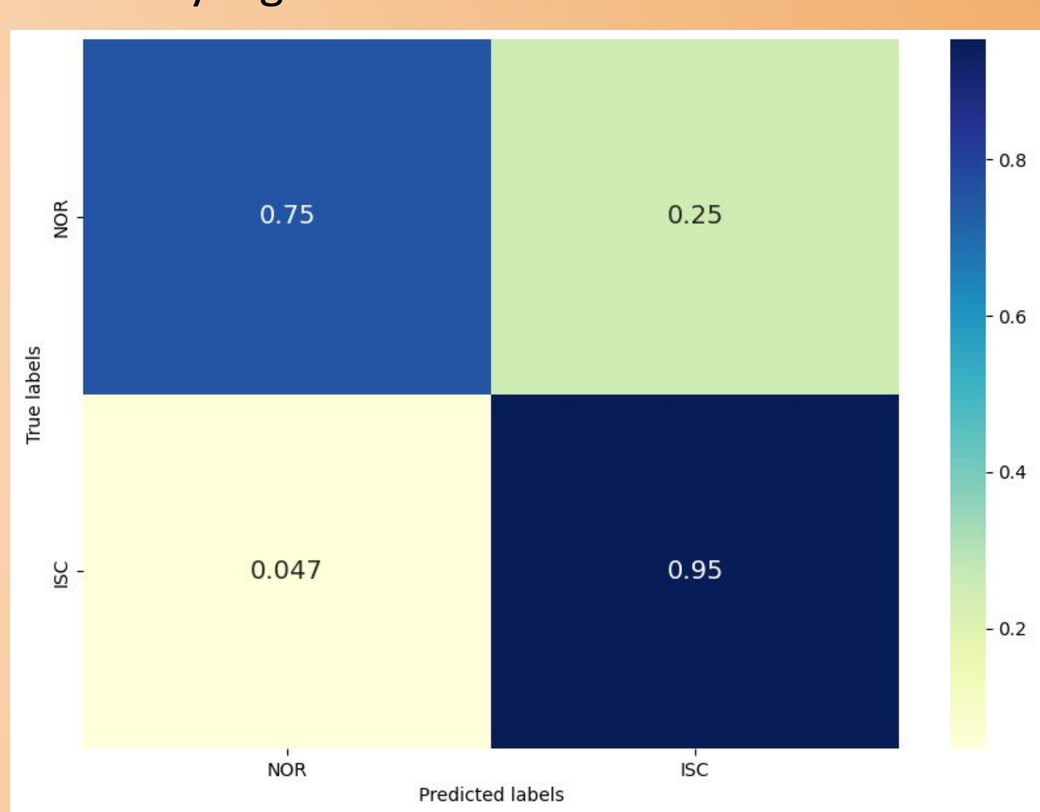


Figure LEFT: We can see the model accuracy and the model loss for both training data and validation data for ECG200.

Figure RIGHT: We can see the confusion matrix for the two classes of the ECG200 dataset.



Convolutional Echo State Network could be used also in physics data analysis, in particular when we are dealing with data that show temporal dependencies, autocorrelation or seasonal variations. An example is the Auger experiment, which data consist of the Flash Analogue-to-Digital Converters (FADCs) associated with each photomultiplier tubes (PMT) and the time of arrival of each stations. With CESN would be possible to reconstruct the energy and the arrival direction of the primary particle. This should guarantee a better performance compared to other algorithm also used for TSC task. These studies are still in progress.

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[4] https://www.timeseriesclassification.com/