

Deep Learning for Time Series Classification and Extrinsic Regression: A Current Survey

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Time Series Classification and Extrinsic Regression are important and challenging machine learning tasks. Deep learning has revolutionized natural language processing and computer vision and holds great promise in other fields such as time series analysis where the relevant features must often be abstracted from the raw data but are not known a priori. This paper surveys the current state of the art in the fast-moving field of deep learning for time series classification and extrinsic regression. We review different network architectures and training methods used for these tasks and discuss the challenges and opportunities when applying deep learning to time series data. We also summarize two critical applications of time series classification and extrinsic regression, human activity recognition and satellite earth observation.

Additional Key Words and Phrases: Deep Learning, Time series, Classification, Extrinsic regression, Review

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1 INTRODUCTION

Time series analysis has been identified as one of the ten most challenging research issues in the field of data mining in the 21st century [1]. Time series classification (TSC) is a key time series analysis task [2]. TSC aims to build a machine learning model that predicts categorical class labels for data consisting of ordered sets of real-valued attributes. There are many applications that require time series analysis such as human activity recognition [3–5], diagnosis based on electronic health records [6, 7], and systems monitoring problems [8]. Additionally, the variety of dataset types in the University of California, Riverside (UCR) [9] and University of East Anglia (UEA) [8] benchmark archive illustrates the wide range of applications of the TSC problem. Time series extrinsic regression (TSER) [10] is the counterpart of TSC for which the output is numeric rather than categorical. It should be noted that the TSER is not a forecasting method

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but rather a method for understanding the relationship between the time series and the extrinsic variable. TSER is an emerging field with great potential to be used in a wide range of applications.

Deep learning has been very successful in various domains, especially computer vision and natural language processing. Many modern applications have started integrating deep learning as part of their system and modeling process. One of the strengths of deep learning relative to more conventional machine learning is its capacity to construct novel features from the low-level properties of the data. In consequence there has been substantial recent focus on deep learning for TSC and TSER. As the relevant features for TSC and TSER are often not known, there is great potential for deep learning to improve upon the state of the art. A highly influential review paper on deep learning-based TSC [11] was published in 2019. However, the field of research is very fast moving, and that prior survey does not cover the current state of the art. For example, it does not include InceptionTime [12], a system that consistently outperforms ResNet [13], the best performing system from the prior survey. Nor does it cover attention models, which have received huge interest in recent years and shown excellent capacity to model long-range dependencies in sequential data, and are well suited for time-series modeling [14–16]. Many attention variants have been proposed to address particular challenges in time series modeling and have been successfully applied to time series classification [17, 18]. In light of the emergence of attention mechanisms and various new network configurations for time series classification, a systematic and comprehensive survey on deep learning in time series classification would greatly benefit the time series community.

This article aims to fill that gap by summarizing recent developments in deep learning-based time series analytics, specifically TSC and TSER. Following definitions and a brief introduction to the time series classification and extrinsic regression tasks, we propose a new taxonomy from both network configuration and application domain perspectives. Various architectures, including multilayer perceptrons (MLP), convolution neural networks (CNN), recurrent neural networks (RNN), and attention-based models, are discussed, along with refinements made to improve performance. We also summarize two key applications of TSC and TSER, Human Activity Recognition and Earth Observation.

2 BACKGROUND AND DEFINITIONS

This section begins by providing the necessary definitions and background information to understand the topic of training deep neural networks (DNNs) for time series classification (TSC) and time series extrinsic regression (TSER) tasks. We begin by defining key terms and concepts, such as time series data and time series supervised learning. To further enhance understanding of the background of time series classification, we provide an overview on the classic non-deep learning models that have been used for this task. Finally, we present our proposed taxonomy of the different DNNs that have been used for TSC and TSER tasks.

2.1 Time series

Time series data are sequences of data points indexed by time.

Definition 2.1. A time series X is an ordered collection of T pairs of measurements and timestamps, $X = \{(x_1, t_1), (x_2, t_2), \dots, (x_T, t_T)\}$, where $x_i \in \mathbb{R}^D$ and t_1 to t_T are the timestamps for some measurements x_1 to x_T .

Each x_i is a D -dimensional vector of values, one for each feature captured in the series. When $D = 1$ the series is called *univariate*. When $D > 1$ the series is called *multivariate*.

2.2 Time series supervised learning tasks

In this paper, we focus on two time series learning tasks, time series extrinsic regression and time series classification. Classification and regression are both supervised learning tasks that learn the relationship between a target variable and a set of time series. We consider learning from a dataset $D = \{(X_1, Y_1), (X_2, Y_2), \dots, (X_N, Y_N)\}$ of N time series where Y_i denotes the target variable for each X_i . It is important to note that for ease of exposition, we sometimes assume in our discussion that the series are of the same length, but most methods extend trivially to the case of unequal-length series. The main difference between TSER and TSC is that TSC predicts a categorical value for a time series that categorises the time series data into some finite categories, while TSER predicts a continuous value. Typically Y_i is a one hot encoded vector for TSC or a numeric value for TSER.

In the context of deep learning, a supervised learning model is a neural network that performs the following functions to map the input time series to a target variable:

$$f_L(\theta_L, \mathbf{X}) = f_{L-1}(\theta_{L-1}, f_{L-2}(\theta_{L-2}, \dots, f_1(\theta_1, \mathbf{X}))) \quad (1)$$

where f_l denotes the non-linear function applied at layer l . The aim of TSC is then to train the neural network model to map a time series dataset D to a set of class labels Y with C class labels. After training, the neural network outputs a vector of C values that estimates the probability of a series X belonging to each class. This is typically achieved using the softmax activation function in the final layer of the neural network. The softmax function estimates probabilities for all of the dependent classes such that they always sum to 1 across all classes. The cross-entropy loss is commonly used for training neural networks with softmax outputs or classification type neural networks.

On the other hand, TSER trains the neural network model to map a time series dataset D to a set of numeric values Y . Instead of outputting probabilities, a regression neural network outputs a numerical value for the time series. It is typically used with a linear activation function in the final layer of the neural network. However, any non linear functions with a single value output such as sigmoid, or ReLU can also be used. A regression neural network typically trains using the mean square error or mean absolute error loss function. Depending on the distribution of the target variable and the choice of final activation functions, different loss functions can be used too.

2.3 TSC and TSER

TSC is a fast-growing field, with hundreds of papers being published every year [8, 9, 11, 19, 20]. Most deep learning approaches to this task have real-valued outputs that are mapped to a class label. Time series extrinsic regression (TSER) [10, 21] is a less widely studied task in which the predicted values are numeric, rather than categorical. As most deep learning approaches to TSC produce numeric values as the penultimate step before reinterpretation as categorical values, most deep learning TSC architectures can be directly applied to TSER with trivial modification. While the majority of the architectures covered in this survey were designed for TSC, it is important to note that it is trivial to adapt most of them for TSER.

Research in TSC started with distance-based approaches that find discriminating patterns in the shape of the time series. Distance-based approaches usually consists of coupling a 1-nearest neighbour (1NN) classifier with a time series distance measure [22, 23]. Small distortions in the time series can lead to false matches when measuring the distance between time series using standard distance measurements such as Euclidean distance [22]. A time series distance measure aims to compensate for these distortions by aligning two time series such that the alignment cost between the two are minimised. There are many time series distances proposed in the literature; among these, the Dynamic Time

Warping (*DTW*) distance is one of the most popular choices for many time series tasks, due to its intuitiveness and effectiveness in aligning two time series. The work in [22] compared several distance measures and showed that as of 2015, there was no single distance that significantly outperformed *DTW* when used with a 1NN classifier. The recent Amerced *DTW* [24] distance is the first distance that is significantly more accurate than *DTW*. These individual 1NN classifiers with different distances can be ensembled together to create an ensemble, such as the Ensemble of Elastic distances (EE), that significantly outperforms each of them individually [22, 23]. However, since most distances have a complexity of $O(L^2)$ where L is the length of the series, performing a nearest neighbour search becomes very costly. Hence, distance-based approaches are considered to be one of the slowest methods for TSC [25, 26].

As a result of EE, recent studies have focused mainly on developing ensembling methods that notably outperform NN-*DTW* [23, 25–35]. These approaches use either an ensemble of tree-based approaches [34, 35] or an ensemble of different types of discriminant classifiers, such as NN with several distances and Support Vector Machine (SVM) on one or several feature spaces [27, 30–32]. All these approaches significantly outperform the NN-*DTW* [19] and share a common property – the data transformation phase where the time series is transformed into a new feature space such as the shapelets transform [31] or *DTW* features [30]. Taking advantage of this notion led to the development of the Hierarchical Vote Collective of Transformation-based Ensembles (HIVE-COTE) [26, 29]. HIVE-COTE is a meta ensemble for TSC and forms its ensemble from classifiers of multiple domains. Since its introduction in 2016 [29], HIVE-COTE has gone through a few iterations. The version used in the MTSC benchmark [20] comprised of 4 ensemble members – Shapelet Transform Classifier (STC), Time Series Forest (TSF), Contractable Bag of Symbolic Fourier Approximation Symbols (CBOSS) and Random Interval Spectral Ensemble (RISE), each of them being the then state of the art in their respective domains. Recently, the latest HIVE-COTE version, HIVE-COTEv2.0 (HC2) was proposed [26]. It is currently one of the most accurate classifiers for both univariate and multivariate TSC tasks [26]. HC2 keeps STC, while replacing the rest of its components with DrCIF, Temporal Dictionary Ensemble (TDE) and Arsenal (an ensemble of 25 ROCKET [36] classifiers with less number of kernels). Despite being the most accurate on 26 benchmark MTSC datasets, that are relatively small, HC2 scales poorly on large datasets with long time series as well as datasets with large numbers of channels.

The field of deep learning has made significant progress in recent years [37, 38], which has led researchers to explore deep learning for solving complex problems in TSC. Deep learning-based TSC methods can be classified into two main types: generative and discriminative [39].

In the TSC community, generative methods are often considered model-based [19], aiming to find an appropriate time series representation before training a classifier. Stacked denoising auto-encoders (SDAE) have been proposed by Bengio et al. [40] to identify the salient structure of input data distributions, and Hu et al. [41] used the same model for the pre-training phase before training a classifier for time series tasks. A universal neural network encoder has been developed to convert variable-length time series to a fixed-length representation [42]. Also, a Deep Belief Network (DBN) combined with a transfer learning method was used in an unsupervised manner to model the latent features of time series [43]. A raw time series was also reconstructed using an Echo State Network (ESN) to learn the appropriate representation prior to training the classifier [44]. Often, implementing generative methods is more complex due to an additional step of unsupervised training. Furthermore, generative methods are typically less efficient than discriminative methods, which directly map raw time series to class probability distributions. Due to these barriers, researchers tend to focus on discriminative methods. This survey mainly focuses on the end-to-end discriminative approaches since raw time series are fed directly to the deep learning models without any heavy pre-processing.

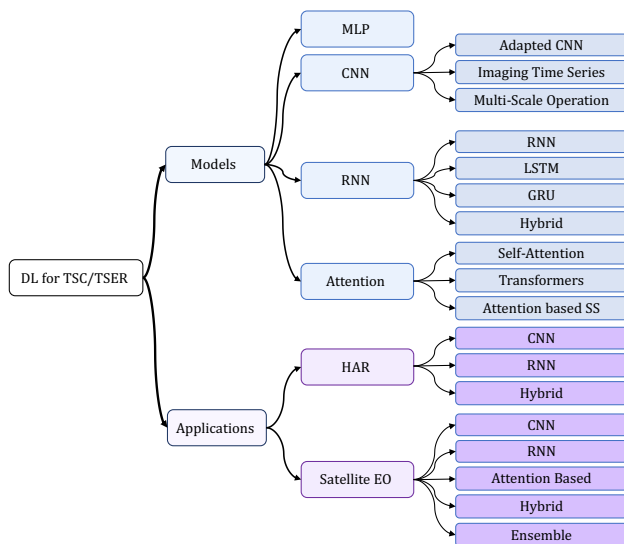


Fig. 1. Taxonomy of Deep Learning (DL) for TSC/TSER from the perspectives of network configuration and application domains.

2.4 Taxonomy of Deep Learning in TSC and TSER

To provide an organized summary of the existing deep learning models for time series classification, we propose a taxonomy that categorizes these models based on their network configurations and application domains. This taxonomy is illustrated in Fig. 1, and it is discussed in sections 3 and 4 of this paper. In section 3, we review various network architectures used for time series classification, including multilayer perceptrons, convolutional neural networks, recurrent neural networks, and attention-based models. We also discuss refinements made to these models to improve their performance on time series tasks. In addition to the network architectures, we summarize key applications of time series classification and extrinsic regression in section 4 of this paper. These applications include human activity recognition and satellite earth observation, which are important and challenging tasks that can benefit from the use of deep learning models. Overall, our proposed taxonomy and the discussions in these sections provide a comprehensive overview of the current state of the art in deep learning for time series analysis and outline future research directions.

Note that we did not include graph neural networks (GCN) in the taxonomy because they are very application-specific and are not applicable to most general time series. Furthermore, there are only a handful of work that apply GCN to TSC and TSER tasks which we will briefly summarise here. GCNs are most commonly used with electroencephalogram (EEG) data where the location of EEG electrodes on our head can be represented naturally using a graph, instead of treating the EEG signal as a multivariate time series. Some of these applications are epilepsy detection [45], seizure detection [46] and sleep classification [47] Besides EEG, GCNs have also been applied to engineering applications such as machine fault diagnosis [48], slope deformation prediction [49] and seismic activity prediction [50]. Applications that use GCN to model their time series, such as the above, often require the time series to have multiple dimensions that makes sense spatially, such as EEG and sensors placed in the ground.

3 DEEP LEARNING MODELS

This section reviews the deep learning-based models for time series classification and discusses their architectures by highlighting their strengths as well as limitations.

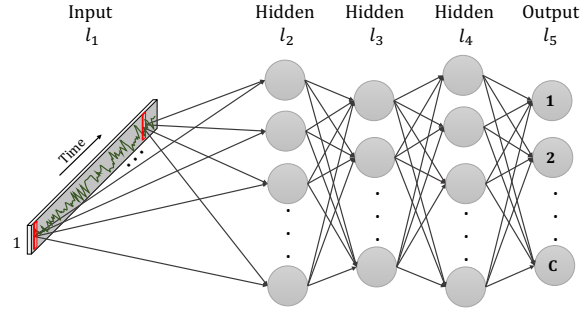


Fig. 2. Multilayer perceptron for univariate time series classification.

3.1 Multi-Layer Perceptron (MLP)

The most straightforward Neural Network architecture is a fully connected network (FC), also called a multilayer perceptron (MLP). As shown in Fig. 2 all neurons of one layer $l - 1$ are connected to all neurons of the following layer l with $l \in [1, L]$. The weights model these connections in a neural network. A general equation for applying a non-linearity to an input A^{l-1} is:

$$A^l = f(W^l \times A^{l-1} + b) \quad (2)$$

where A^l the activation of the neurons in layer l where A^1 is equal to input series X . Also, W and b are the neuron weights and bias, and f is the nonlinear activation function. The number of layers and neurons are defined as hyperparameters in MLP models. However, studies such as auto-adaptive MLP [51] have attempted to determine the number of neurons in the hidden layers automatically, based on the nature of the training time series data. This allows the network to adapt to the training data's characteristics and optimize its performance on the task at hand.

One of the main limitations of using multilayer perceptrons (MLPs) for time series data is that they are not well-suited to capturing the temporal dependencies in this type of data. MLPs are feedforward networks that process input data in a fixed and predetermined order without considering the temporal relationships between the input values. As shown in Fig. 2, each time step is weighted individually, and time series elements are treated independently from each other. Various studies used MLPs alongside other feature extractors like Dynamic Time Warping to address this problem [52, 53]. DTW-NN is a feedforward neural network that exploits DTW's elastic matching ability to dynamically align a layer's inputs to the weights instead of using a fixed and predetermined input-to-weight mapping. This weight alignment replaces the standard dot product within a neuron with DTW. In this way, the DTW-NN is able to tackle difficulties with time series recognition, such as temporal distortions and variable pattern length within a feedforward architecture [53]. Similarly, Simple Symbolic Aggregate Approximation (SAX) is used to transform time series into a symbolic representation and produce sequences of words based on the symbolic representation [54]. The symbolic time series-based words are later used as input for training a two-layer MLP for classification.

Although the models mentioned above attempt to resolve the shortage of capturing temporal dependencies in MLP models, they still have other limitations on capturing time-invariant features [13]. Additionally, MLP models do not have the ability to process input data in a hierarchical or multi-scale manner. Time series data often exhibits patterns and structures at different scales, such as long-term trends and short-term fluctuations. MLP models fail to capture these patterns, as they are only able to process input data in a single, fixed-length representation. Many other deep learning models are better suited to handle time series data, such as recurrent neural networks (RNNs) and convolutional neural networks (CNNs), specifically designed to capture the temporal dependencies and patterns in time series data.

3.2 CNN based models

The convolutional neural network (CNN) was first proposed by Kunihiko Fukushima in 1982 [55]. It was inspired by the structure and function of the visual cortex in animals, specifically the cat’s cortex, as described by David Hubel and Torsten Wiesel in their influential work from 1962 [56]. Convolutional neural networks have been widely used for visual pattern recognition, but due to computational resource requirements, were not capable of processing large images before the advent of GPU technology. After developing Graphics Processing Unit (GPU) technology, Krizhevsky et al. [37] implemented an efficient GPU-based program and won the ImageNet competition in 2012, bringing the convolution neural network back into the spotlight.

Many variants of CNN architectures have been proposed in the literature, but their primary components are very similar. Using the LeNet-5 [57] as an example, it consists of three types of layers: convolutional, pooling, and fully connected. The purpose of the convolutional layer is to learn feature representations of the inputs. Fig. 3 shows the architecture of the t-LeNet network, which is a time series-specific version of LeNet. This figure shows that the convolution layer is composed of several convolution kernels (or filters) used to compute different feature maps. In particular, each neuron of a feature map is connected to a region of neighboring neurons in the previous layer called the receptive field. Feature maps can be created by first convolving inputs with learned kernels and then applying an element-wise nonlinear activation function to the convolved results. It is important to note that all spatial locations of the input share the kernel for each feature map, and several kernels are used to obtain the entire feature map. The feature value of the l^{th} layer of k^{th} feature map at location (i, j) is obtained by:

$$Z_{i,j,k}^l = \mathbf{W}_k^{lT} \mathbf{A}_{i,j}^{l-1} + b_k^l \quad (3)$$

Where \mathbf{W}_k^l and b_k^l are the weight vector and bias term of the k^{th} filter of the l^{th} layer, respectively, and $\mathbf{A}_{i,j}^{l-1}$ is the input patch centered at location (i, j) of the l layer. Note that the kernel \mathbf{W}_k^l that generates the feature map $Z_{i,j,k}^l$ is shared. A weight-sharing mechanism has several advantages, such as reducing model complexity and making the network easier to train. Let $f(\cdot)$ denote the nonlinear activation function. The activation value of convolutional feature $Z_{i,j,k}^l$ can be computed as:

$$\mathbf{A}_{i,j,k}^l = f(Z_{i,j,k}^l) \quad (4)$$

The most common activation functions are sigmoid, tanh and ReLU [58]. As shown in Fig. 3, a pooling layer is often placed between two convolution layers to reduce the resolution of the feature maps and to achieve shift-invariance. Following several convolution stages –the block comprising convolution, activation, and pooling is called convolution *stage* – there may be one or more fully-connected layers that aim to perform high-level reasoning. As discussed in section 3.1, each neuron in the previous layer is connected to every neuron in the current layer to generate global semantic information. In the final layer of CNNs, there is the output layer in which the Softmax operators are commonly used for classification tasks [59].

3.2.1 Adapted CNNs for TSC and TSER. Several improvements have been made to CNN since the success of AlexNet in 2012 [37] such as using deeper networks, applying smaller and more efficient convolutional filters, adding pooling layers to reduce the dimensionality of the feature maps, and utilizing batch normalization to improve the stability of training [59]. They have been demonstrated to be very successful in many domains, such as computer vision, speech recognition, and natural language processing problems [38, 59, 60]. As a result of the success of CNN architectures in these various domains, researchers have also started adopting them for time series classification [11, 16, 20, 61]. This section presents the first category, which we refer to as Adapted CNNs for TSC and TSER. The papers discussed here

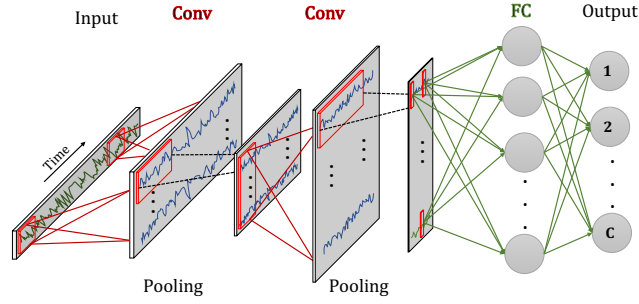


Fig. 3. The architecture of the t-LeNet network (time series specific version of LeNet)

are mostly adaptations without any particular preprocessing or mathematical characteristics, such as transforming the series to an image or using multi-scale convolution and therefore do not fit into one of the other categories.

A Multi-Channel Deep Convolutional Neural Network (MC-DCNN) [62] employed a CNN for time series classification for the first time. The proposed architecture is mainly a traditional deep CNN with one main modification for multivariate data: the convolutions are independently applied to each channel (input dimension). Each dimension of the input MTS goes through two convolutional stages with the ReLU activation function. A max pooling operation of length 2 follows each convolution. The output from each dimension is concatenated and passed to a fully connected layer which is then fed to a final softmax classifier for classification. Similar to MC-DCNN, a three-layer convolution neural network was proposed for Human activity recognition (MC-CNN)[63]. Unlike the MC-DCNN, this model applies 1D convolutions to all input channels simultaneously to capture the temporal and spatial relationships in the early stages. The 2-stage version of MC-CNN architecture was used by Zhao et al. [64] on the earliest version of the UCR Time Series Data Mining Archive. The authors also conducted an ablation study to evaluate the performance of the CNN models with differing numbers of convolution filters and pooling types.

Fully Convolutional Networks (FCN) [65], and Residual Networks (Resnet) [66] are two deep neural networks that are commonly used for image and video recognition tasks and have been adapted for end-to-end time series classification [13]. FCNs are a variant of convolutional neural networks (CNNs) designed to operate on inputs of arbitrary size rather than being constrained to fixed-size inputs like traditional CNNs. This is achieved by replacing the fully connected layers in a traditional CNN with a Global Average Pooling (GAP) [65]. FCN was adapted for univariate time series classification [13], and similar to the original model, it contains three convolution blocks where each block contains a convolution layer followed by batch normalization and ReLU activation. Each block uses 128, 256, 128 filters with 8, 5, 3 filter lengths respectively. The output from the last convolution block is averaged with a GAP layer and passed to a final softmax classifier. The GAP layer has the property of reducing the spatial dimensions of the input while retaining the channel-wise information, which allows it to be used in conjunction with a class activation map (CAM) [67] to highlight the regions in the input that are most important for the predicted class. This can provide useful insights into how the network is making its predictions and help identify potential improvement areas.

Similar to FCN, the Residual Network (ResNet) was also proposed in [13] for univariate time series classification. ResNet is one of the deepest architectures containing three residual blocks followed by a GAP layer and a softmax classifier. It uses residual connections between each block to reduce the vanishing gradient effect in deep learning models. The structure of each residual block is similar to the FCN architecture, containing three convolution layers followed by batch normalization and ReLU activation. Each convolution layer uses 64 filters with 8, 5, 3 filter lengths,

respectively. ResNet was found to be one of the most accurate deep learning TSC architectures on 85 univariate TSC datasets [11, 19]. Additionally, integration of ResNet and FCN has been proposed to combine the strength of both networks [68].

In addition to adapting the network architecture, some research has focused on modifying the convolution kernel to suit time series classification tasks better. Dilated convolutions neural networks (DCNNs) [69] are a type of CNN that uses dilated convolutions to increase the receptive field of the network without increasing the number of parameters. Dilated convolutions create gaps between elements of the kernel and perform convolution, thereby covering a larger area of the input. This allows the network to capture long-range dependencies in the data, making it well-suited to time series classification tasks [70]. Recently, Disjoint-CNN [71] showed that factorization of 1D convolution kernels into disjoint temporal and spatial components yields accuracy improvements with almost no additional computational cost. Applying disjoint temporal convolution and then spatial convolution behaves similarly to Inverted Bottleneck [72]. Like the Inverted Bottleneck, the temporal convolutions expand the number of input channels, and spatial convolutions later project the expanded hidden state back to the original size to capture the temporal and spatial interaction.

3.2.2 Imaging time series. In time series classification, a common approach is to convert the time series data into a fixed-length representation, such as a vector or matrix, which can then be input to a deep learning model. However, this can be challenging for time series data that vary in length or have complex temporal dependencies. One solution to this problem is to represent the time series data in an image-like format, where each time step is treated as a separate channel in the image. This allows the model to learn from the spatial relationships within the data rather than just the temporal relationships. In this context, the term *spatial* refers to the relationships between different variables or features within a single time step of the time series.

As an alternative to using raw time series data as input, Wang and Oates encoded univariate time series data into different types of images that were then processed by a regular CNN [73]. This image-based framework initiated a new branch of deep learning approaches for time series, which consider image transformation as one of the feature engineering techniques. Wang and Oates presented two approaches for transforming a time series into an image. The first generates a Gramian Angular Field (GAF), while the second generates a Markov Transition Field (MTF). GAF represents time series data in a polar coordinate and uses various operations to convert these angles into a symmetry matrix and MTF encodes the matrix entries using the transition probability of a data point from one time step to another time step [73]. In both cases, the image generation increases the time series size, making the images potentially prohibitively large. Therefore they propose strategies to reduce their size without losing too much information. Afterward, the two types of images are combined in a two-channel image that is then used to produce better results than those achieved when using each image separately. Finally, a Tiled CNN model is applied to classify the time-series images. In other studies, a variety of transformation methods, including Recurrence Plots (RP) [74], Gramian Angular Difference Field (GADF) [75], bilinear interpolation [76], and Gramian Angular Summation Field (GASF) [77] have been proposed to transfer time series to input images expecting that the two-dimensional images could reveal features and patterns not found in the one-dimensional sequence of the original time series.

Hatami et al. [74] propose a representation method based on RP [78] to convert the time series to 2D images with a CNN model for TSC. In their study, time series are regarded as distinct recurrent behaviors such as periodicities and irregular cyclicities, which are the typical phenomenon of dynamic systems. The main idea of using the RP method is to reveal at which points some trajectories return to a previous state. Finally, two-stage convolution and two fully connected layers are applied to classify the images generated by RP. Later with the emerging better architecture in the

Model	Year	Baseline Architecture	Other features
Adapted			
MC-DCNN [62]	2014	2-Stage Conv	Independent convolutions per Channel
MC-CNN [63]	2015	3-Stage Conv	1D-Convolutions on all Channel
Zhao et al. [64]	2015	2-Stage Conv	Similar architecture to MC-CNN
FCN [13]	2017	FCN	Using GAP instead of FC Layer
ResNet [13]	2017	ResNet 9	Using 3-Residual block
Res-CNN [68]	2019	ResNet+FCN	Using 1-Residual block + FCN
DCNNs [70]	2019	4-Stage Conv	Using dilated convolutions
Disjoint-CNN [13]	2021	4-Stage Conv	Disjoint temporal and spatial convolution
Series To Image			
Wang&Oates[73]	2015	Tiled CNN	Gramian Angular Field, Markov Transition Field
Hatami et al.[74]	2017	2-Stage Conv	Recurrence Plots
Karimi et al.[75]	2018	Inception V3	Gramian Angular Difference Field
Zhao et al. [76]	2019	ResNet18, ShuffleNet V2	Bilinear interpolation
RPMCNN [80]	2019	VGGNet, 2-Stage Conv	Relative Position Matrix Gramian Angular Summation Field, Gramian AngularDifference Field, Markov Transition Field
Yang et al. [77]	2019	VGGNet	
Multi-Scale Operation			
MCNN [81]	2016	2-Stage Conv	Identity mapping, Smoothing, Down-sampling
t-LeNet [82]	2016	2-Stage Conv	Squeeze and Dilation
MVCNN [83]	2019	4-stage Conv	Inception V1 based
Brunel et al. [84]	2019	Inception V1	
InceptionTime [12]	2019	Inception V4	Ensemble
EEG-inception [85]	2021	InceptionTime	
Inception-FCN [86]	2021	InceptionTime + FCN	
KDCTime [87]	2022	InceptionTime	Knowledge Distillation, Label smoothing

Table 1. Summary of CNN models for time series classification and extrinsic regression

computer vision domain, pre-trained Inception v3 [79] was used to map the GADF images into a 2048-dimensional vector space. In the final stage, a multilayer perceptron (MLP) is used with three hidden layers, and a softmax activation function for classification [75]. Following the same framework, Chen and Shi [80] adopted the Relative Position Matrix and VGGNet (RPMCNN) in order to classify time series data using transform 2D images. Their results showed promising performances by converting univariate time series data to 2D images using relative positions between two-time stamps. Following the convention, three image encoding methods: GASF, GADF, and MTF, were used to encode MTS data into two-dimensional images [77]. They showed that the simple structure of ConvNet is sufficient enough for classification as it performed equally well with the complex structure of VGGNet.

Overall, representing time series data as 2D images can be difficult because preserving the temporal relationships and patterns in the data can be challenging. This transformation can also result in a loss of information, making it difficult for the model to classify the data accurately. Chen and Shi [80] have also shown that the specific transformation methods like GASF, GADF, and MTF used in this process do not significantly improve the prediction outcome.

3.2.3 Multi-Scale Operation. The papers discussed here apply a multi-scale convolutional kernel to the input series or apply regular convolutions on the input series at different scales. Multi-scale Convolutional Neural Networks (MCNN) [81] and Time LeNet (t-LeNet Fig. 3) [82] were considered the first models that preprocess the input series to apply

convolution on multi-scale series rather than raw series. The design of both MCNNs and t-LeNet were inspired by computer vision models, which means that they were adapted from models originally developed for image recognition tasks. These models may not be well-suited to time series classification tasks and may not perform as well as models specifically designed for this purpose. One potential reason for this is the use of progressive pooling layers (see Fig. 3) in these models, commonly used in computer vision models, to reduce the input data size and make it easier to process. However, these pooling layers may not be as effective when applied to time series data and may limit the performance of the model.

As with a traditional CNN model, MCNN has simple architecture and comprises two convolutions and a pooling layer, followed by a fully connected and softmax layer. However, this approach involves heavy data preprocessing. Specifically, before any training, they use a sliding window to extract a time series subsequence, and later, the subsequence will undergo three transformations: (1) identity mapping, (2) down-sampling, and (3) smoothing, which results in the transformation of a univariate input time series into a multivariate one. Finally, the transformed output is fed to the CNN model to train a classifier [81]. t-LeNet uses two data augmentation techniques: window slicing (WS) and window warping (WW), to prevent overfitting [82]. The WS method is identical to MCNN's data augmentation. The second data augmentation technique, WW, employs a warping technique that squeezes or dilates the time series. WS is also adopted to ensure that subsequences of the same length are extracted for training the network to deal with multi-length time series. Therefore, a given input time series of length L is first dilated ($\times 2$) and then squeezed ($\times 1/2$) using WW, resulting in three time series of length L , $2L$, $1/2L$ that are fed to WS to extract equal length subsequences for training. Finally, as both MCNN and t-LeNet predict a class for each extracted subsequence, majority voting is applied to obtain the class prediction for the full time series.

Inception was first proposed by Szegedy et al. [88] for end-to-end image classification. Now the network has evolved to become Inception-v4, where Inception was coupled with residual connections to improve further the performance [89]. Inspired by inception architecture, a multivariate convolutional neural network (MVCNN) is designed using multi-scale convolution kernels to find the optimal local construction [83]. MVCNN uses three scales of filters, including 2×2 , 3×3 , and 5×5 , to extract features of the interaction between sensors. A one-dimensional Inception model was used for Supernovae classification using the light flux of a region in space as an input MTS for the network [84]. However, the authors limited the conception of their Inception architecture to the first version of this model [88]. The Inception-ResNet [90] architecture includes convolutional layers, followed by Inception modules and residual blocks. The Inception modules are used to learn multiple scales and aspects of the data, allowing the network to capture more complex patterns. The residual blocks are then used to learn the residuals, or differences, between the input and output of the network, improving its performance.

InceptionTime [12] explores much larger filters than any previously proposed network for TSC in order to reach state-of-the-art performance on the UCR benchmark. InceptionTime is an ensemble of five randomly initialised inception network models, each of which consists of two blocks of inception modules. Each inception module first reduces the dimensionality of a multivariate time series using a bottleneck layer with length and stride of 1 while maintaining the same length. Then, 1D convolutions of different lengths are applied to the output of the bottleneck layer to extract patterns at different sizes. In parallel, a max pooling layer followed by a bottleneck layer are also applied to the original time series to increase the robustness of the model to small perturbations. The output from the convolution and max pooling layers are stacked to form a new multivariate time series which is then passed to the next layer. Residual connections are used between each inception block to reduce the vanishing gradient effect. The output of the second inception block is passed to a GAP layer before feeding into a softmax classifier.

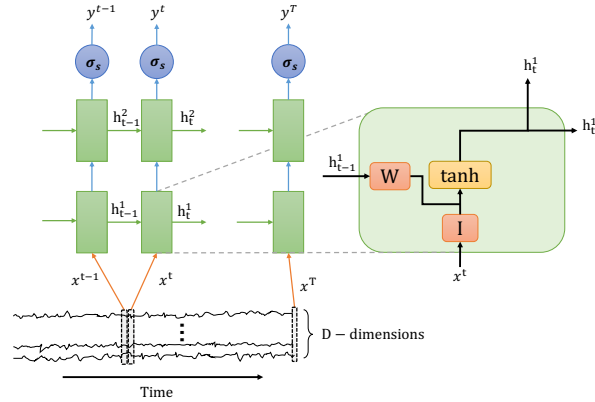


Fig. 4. The architecture of two layer Recurrent Neural Network

Due to the favorable performance of InceptionTime for time series classification, various extensions such as EEG-inception [85], InceptionFCN [86], and KDCTime [87] have been proposed. Like InceptionTime, EEG-inception uses several inception layers and residual connections as its backbone. Also, to tackle the limitation in the training data, noise addition-based data augmentation of EEG signals is proposed, which increases the average accuracy. InceptionFCN focuses on combining two well-known deep learning techniques, namely the Inception module and the Fully Convolutional Network [86]

In KDCTime [87], the authors first proposed label smoothing for InceptionTime (LSTime), which uses the soft label information instead of only hard labels. Next, instead of manually adjusting soft labels by LSTime, knowledge distillation for InceptionTime (KDTime) is proposed to automatically generate soft labels by the teacher model while compressing the inference model. Finally, to rectify the incorrectly predicted soft labels from the teacher model, knowledge distillation with calibration (KDC) for InceptionTime (KDCTime) is proposed, which contains two optional calibrating strategies, i.e., KDC by translating (KDCT) and KDC by reordering (KDCR).

3.3 Recurrent Neural Network

3.3.1 Recurrent Neural Networks (RNNs). RNNs are types of neural networks that are specifically designed to process time series and other sequential data. RNNs are conceptually similar to feed-forward neural networks (FFNs). While FFNs map from fixed-size inputs to fixed-size outputs, RNNs can process variable-length inputs and produce variable-length outputs. This capability is enabled by sharing parameters over time through directed connections between individual layers. RNN models for time series classification can be classified as sequence to sequence or sequence-to-one based on their outputs. Fig. 4 shows sequence to sequence architectures for RNN models, with an output for each input sub-series. On the other hand, in sequence-to-one architecture, decisions are made using only y^T and ignoring the other outputs.

At each time step t , RNNs maintain a hidden vector h which updates as follows [91, 92]:

$$h_t = \tanh(W h_{t-1} + I x^t) \quad (5)$$

Where $X = \{x^1, \dots, x^{t-1}, x^t, \dots, x^T\}$ contains all of the observation, \tanh denotes the hyperbolic tangent function, and the recurrent weight and the projection matrix are shown by W and I , respectively. The hidden-to-hidden connections

also model the short-term time dependency. The hidden state h is used to make a prediction as:

$$y^t = \sigma_s(Wh_{t-1}) \quad (6)$$

where σ_s is a softmax function and provides a normalized probability distribution over the possible classes. As depicted in Fig. 4, the hidden state h can be used to stack RNNs in order to build deeper networks:

$$h_t^l = \sigma(Wh_{t-1}^l + Ih_{t-1}^{l-1}) \quad (7)$$

where σ is the logistic sigmoid function. As an alternative to feeding each time step to the RNN, the data can be divided into time windows of ω observations, each overlapping by 0 - 50 percent of ω . Each time window is labeled with the majority response labels within the ω window.

Recurrent neural networks for time series classification have been proposed in [93]. Using RNNs, the input series have been classified based on their dynamic behavior. They used sequence-to-sequence architecture in which each sub-series of input series is classified in the first step. Then the argmax function is applied to the entire output, and finally, the neuron with the highest rate specifies the classification result. In order to improve the model parallelization and capacity [94] proposed a two-layer RNN. In the first layer, the input sequence is split into several independent RNNs to improve parallelization, followed by a second layer that utilizes the first layer's output to capture long-term dependencies [94]. Further, RNNs have been used in some hierarchical architectures [95, 96]. Hermans and Schrauwen showed a deeper version of recurrent neural networks could perform hierarchical processing on complex temporal tasks and capture the time series structure more naturally than a shallow version [96]. RNNs are usually trained iteratively using a procedure known as backpropagation through time (BPTT). When unfolded in time, RNNs look like very deep networks with shared parameters. With deeper neural layers in RNN and sharing weights across different RNN cells, the gradients are summed up at each time step to train the model. Thus, gradients undergo continuous matrix multiplication due to the chain rule and either shrink exponentially and have small values called vanishing gradients or blow up to a very large value, referred to as exploding gradients [97]. These problems motivated the development of second-order methods for deep architectures named long short-term memory (LSTM) [98] and Gated Recurrent Unit (GRU) [99].

3.3.2 Long Short Term Memory (LSTM). LSTM deals with the vanishing/exploding gradient problem commonly found in standard recurrent neural networks through the incorporation of gate-controlled memory cells into their state dynamics [98]. An LSTM uses a hidden vector h and a memory vector m to control state updates and outputs for each time step. Specifically, the computation at time step t is formulated as follows [100]:

$$\begin{aligned} \Gamma^c &= \tanh(W^c h_{t-1} + I^c x^t) \\ \Gamma^u &= \sigma(W^u h_{t-1} + I^u x^t) \\ \Gamma^f &= \sigma(W^f h_{t-1} + I^f x^t) \\ \Gamma^o &= \sigma(W^o h_{t-1} + I^o x^t) \\ m_t &= \Gamma^f \otimes m_{t-1} + \Gamma^u \otimes \Gamma^c \\ h_t &= \tanh(\Gamma^o \otimes m_t) \end{aligned} \quad (8)$$

where Γ^c is a cell state gate and Γ^u , Γ^f and Γ^o are the activation vector of the input, forget and output gate respectively. σ is the logistic sigmoid function and \otimes shows the element-wise product. W^u , W^f , W^o , W^c represent the recurrent weight matrices, and I^u , I^f , I^o , I^c represent the projection matrices.

Due to its design nature, LSTM is suited to problems involving sequence data, such as language translation [101], video representation learning [102], and image caption generation [103]. The time series classification problem is not an exception and mainly adopts a similar model to the language translation [101]. S2SwA [104] incorporates two LSTMs, one encoder and one decoder, in a sequence-to-sequence fashion for time series classification. In this model, the encoder LSTM accepts input time series of arbitrary lengths and extracts information from the raw data based on which the decoder LSTM constructs fixed-length sequences that can be regarded as automatically extracted features for classification.

3.3.3 *Gated Recurrent Unit (GRU)*. is another widely-used variant of RNNs, and similar to LSTM it can control the flow of information like memorizing the context over multiple time steps [99]. While GRU was introduced later than LSTM, it has a simpler architecture. Compared to LSTMs, GRUs have two gates, reset and update gates, which are more computationally efficient and require fewer data to generalize and defined as follows:

$$\begin{aligned}
 \Gamma^z &= \sigma(W^z h_{t-1} + I^z x^t) \\
 \Gamma^r &= \sigma(W^r h_{t-1} + I^r x^t) \\
 \tilde{h}_t &= \tanh(W[h_{t-1} \otimes \Gamma^r, x^t]) \\
 h_t &= (1 - \Gamma^z) \otimes h_{t-1} + \Gamma^z \otimes \tilde{h}_t
 \end{aligned} \tag{9}$$

Similar to S2SwA [104] sequence auto-encoder (SAE) based on GRU has define to deal with time series classification problem [105]. A fixed-size output is produced by processing the various input lengths using GRU as the encoder and decoder. The model’s accuracy was also improved by pre-training the parameters on massive unlabeled data.

3.3.4 *Hybrid Models*. CNN’s and RNNs are often combined for time series classification because they have complementary strengths that can improve the model’s performance. As mentioned previously, CNNs are well-suited for learning from spatial relationships in data, such as the patterns and correlations between the channels of different time steps in a time series. This allows them to learn useful features from the time series data that can help improve the classification performance. RNNs, on the other hand, are well-suited for learning from temporal dependencies in data, such as the past values of a time series that can help predict its future values. This allows them to capture the dynamic nature of time series data and make more accurate predictions. Combining the strengths of CNNs and RNNs makes it possible to learn spatial and temporal features from the time series data, improving the model’s performance for time series classification. Additionally, the two models can be trained together, allowing them to learn from each other and improve the model’s overall performance.

Various extensions like MLSTM-FCN [106], TapNet [107], and SMATE [108] were proposed later to deal with time-series data. MLSTM-FCN extends the univariate LSTM-FCN model [109] to the multivariate case. Like the LSTM-FCN, the multivariate version comprises LSTM blocks and fully convolutional blocks for extracting features from input series. A squeeze and excite block is also added to the FCN block, and can execute a form of self-attention on the output feature maps of previous layers [106]. Two further proposals for multivariate time series classification are the Time series attentional prototype Network (TapNet) and Semi-Supervised Spatio-Temporal (SMATE) [107, 108]. These methods combine and seek to leverage the relative strengths of both traditional distance-based and deep-learning approaches.

MLSTM-FCN, TapNet, and SMATE were designed in dual-network architectures. The input is separately fed into the CNN and RNN models, and their output is concentrated before the fully connected layer for the final task. However, one branch cannot fully use the hidden states of the other during feature extraction since the final classification results

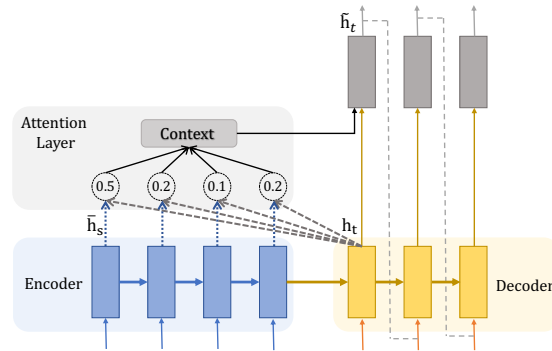


Fig. 5. Self-Attention mechanism

are generated by concatenating the outputs of the two branches. That motivates different types of architecture that try layer-wise integration of CNN and RNN models. This motivates different architectures, such as GCRNN [110] and CNN-LSTM [111], that try layer-wise integration of CNNs and RNNs.

While recurrent neural networks are commonly used for time series forecasting, only a few studies have applied them to time series classification, mainly due to four reasons:

- (1) RNNs typically struggle with the gradient vanishing and exploding problem due to training on long-time series [112].
- (2) RNNs are considered difficult to train and parallelize, so researchers are less likely to use them as they are computationally expensive [97].
- (3) Recurrent architectures are designed mainly to learn from the previous data to make predictions about the future [39].
- (4) RNN models can fail to effectively capture and utilize long-range dependencies in long sequences [104].

3.4 Attention based model

As we mentioned earlier, CNNs have been the most successful deep learning architecture for various applications, including computer vision, natural language processing, and speech recognition [37, 38]. Despite the excellent performance of CNN models for capturing local temporal/spatial correlations, these models can not effectively capture and utilize long-range dependencies. Additionally, they only consider the local order of data points rather than the overall order of all data points. Therefore, many recent studies have embedded recurrent neural networks (RNN) such as LSTMs alongside the CNNs to capture this information [106, 107, 109]. The disadvantage of RNN-based models is that they are computationally expensive, and their capability to capture long-range dependencies is limited [17, 113].

On the other hand, *attention models* can capture long-range dependencies, and their broader receptive fields provide more contextual information, which can improve the models' learning capacity. The attention mechanism aims to enhance a network's representation ability by focusing on essential features and suppressing unnecessary ones. Not surprisingly, with the success of *attention models* in natural language processing [113, 114], many previous studies have attempted to bring the power of attention models into various domains such as computer vision [115] and time series analysis [14, 15, 17, 18, 116].

3.4.1 Self-Attention. The attention mechanism was introduced by [117] for improving the performance of encoder-decoder models [118] in neural machine translation. The encoder-decoder in neural machine translation encodes a source sentence into a vector in latent space and decodes the latent vector into a target language sentence. As shown in Fig. 5, the attention mechanism allows the decoder to pay attention to the segments of the source for each target through a context vector c_t . For this model, a variable-length attention vector α_t , equal to the number of source time steps, is derived by comparing the current target hidden state h_t with each source hidden state \bar{h}_s as follows [119]:

$$\alpha_t(s) = \frac{\exp(\text{score}(h_t, \bar{h}_s))}{\sum_{s'} \exp(\text{score}(h_t, \bar{h}_{s'}))} \quad (10)$$

The term *score* is referred to as an alignment model and used to compare the target hidden state h_t with each of the source hidden states \bar{h}_s , and the result is normalized to produced attention weights (a distribution over source positions). There are various choices of the scoring function:

$$\text{score}(h_t, \bar{h}_s) = \begin{cases} h_t^T W \bar{h}_s \\ v_\alpha^T \tanh(W_\alpha [h_t; \bar{h}_s]) \end{cases} \quad (11)$$

As shown above, the score function is parameterized as a feedforward neural network that is jointly trained with all the other components of the model. The model directly computes soft attention, allowing the cost function's gradient to be backpropagated [117].

Given the alignment vector as weights, the context vector c_t is computed as the weighted average over all the source hidden state:

$$c_t = \sum_s \alpha_{ts} \bar{h}_s \quad (12)$$

Accordingly, the computation path goes from $h_t \rightarrow \alpha_t \rightarrow c_t \rightarrow \tilde{h}_t$ then make a prediction using a *Softmax* function [119].

Self-attention has been demonstrated to be effective in various natural language processing tasks due to its ability to capture long-term dependencies in text [113]. Recently, it has also been shown to be effective for time series classification tasks [17, 120–122]. As we mentioned, the self-attention module is embedded in the encoder-decoder models to improve the model performance. However, only the encoder and the self-attention module have been used for time series classification. Early models of TSC follow the same backbone of natural language processing models and use the Recurrent-based models such as RNN [123], GRU[120] and LSTM[124, 125] for encoding the input series. For example, the Multi-View Attention Network (MuVAN) applies bidirectional GRUs independently to each input dimension as the encoder and then feeds all the representations into a self-attention block [120].

As a result of the excellent performance of the CNN models, many studies have attempted to encode the time series using CNN before applying attention [17, 121, 126, 127]. Cross Attention Stabilized Fully Convolutional Neural Network (CA-SFCN) [17] and Locality Aware eXplainable Convolutional ATtention network (LAXCAT) [121] applied the self-attention mechanism to leverage the long-term dependencies for the MTSC task. CA-SFCN combines FCN and two types of self-attention - temporal attention (TA) and variable attention (VA), which interact to capture the long-range dependencies and variables interactions. LAXCAT also used temporal and variable attention to identify informative variables and the time intervals where they have informative patterns for classification.

Several self-attention models have been developed to improve network performance [128, 129], including Squeeze-and-Excitation (SE) [130], which focuses on channel attention and is often used to classify time series data [106, 122, 131].

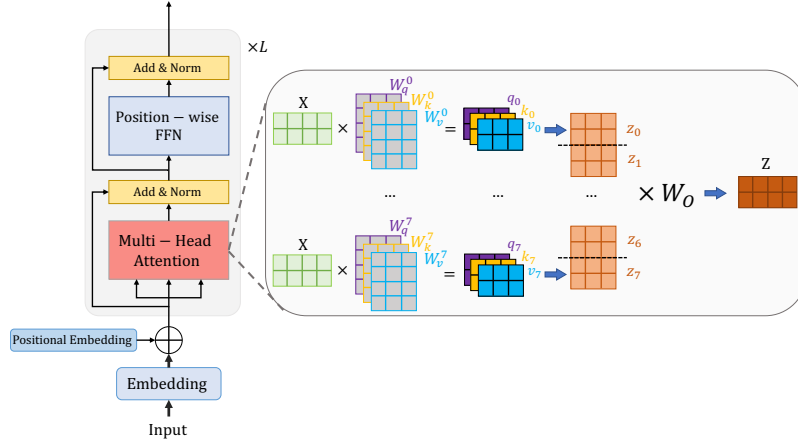


Fig. 6. Multi-head attention block: the example consists of eight heads, and the input sequence comprises two time steps.

The SE block allows the whole network to use global information to selectively focus on the informative feature maps and suppress less important ones [130]. More importantly, the SE block can increase the quality of the shared lower-level representations in the early layers and becomes increasingly specialized when responding to different inputs in later layers. The weight of each feature map is automatically learned at each layer of the network, and the SE block can boost feature discrimination throughout the whole network. Multi-scale Attention Convolutional Neural Network (MACNN) [122] applies the different kernel size convolutions to capture different scales of information along the time axis by generating feature maps at differing scales. Then an SE block is used to enhance useful feature maps and suppresses less useful ones by automatically learning each feature map's importance.

3.4.2 Transformers. Similar to self-attention and other competitive neural sequence models, the original transformer developed for NLP (hereinafter the vanilla transformer) has an encoder-decoder structure that takes as input a sequence of words from the source language and then generates the translation in the target language [113]. Both the encoder and decoder are composed of multiple identical blocks. Each encoder block consists of a multi-head self-attention module and a position-wise feed-forward network (FFN), while each decoder block inserts cross-attention models between the multi-head self-attention module and the position-wise feed-forward network (FFN). Unlike RNNs, Transformers do not use recurrence and instead model sequence information using the positional encoding in the input embeddings.

The transformer architecture is based on finding associations or correlations between various input segments using the dot product. As shown in Fig. 6, the attention operation in transformers starts with building three different linearly-weighted vectors from the input x_i , referred to as query (q_i), key (k_i), and value (v_i):

$$\mathbf{q}_i = W_q \mathbf{x}_i, \quad \mathbf{k}_i = W_k \mathbf{x}_i, \quad \mathbf{v}_i = W_v \mathbf{x}_i \quad (13)$$

where W_q , W_k and W_o learnable weight matrices. The output vectors \mathbf{z}_i are given by:

$$\mathbf{z}_i = \sum_j \text{softmax} \left(\frac{\mathbf{q}_i^T \mathbf{k}_j}{\sqrt{d_q}} \right) \mathbf{v}_j \quad (14)$$

Note that the weighting of the value vector \mathbf{v}_j depends on the mapped correlation between the query vector \mathbf{q}_i at position i and the key vector \mathbf{k}_j at position j . The value of the dot product tends to grow with the increasing size of

the query and key vectors. As the softmax function is sensitive to large values, the attention weights are scaled by the square root of the size of the query and key vectors d_q . The input data may contain several levels of correlation information, and the learning process may benefit from processing the input data in multiple different ways. Multiple attention heads are introduced that operate on the same input in parallel and use different weight matrices W_q, W_k , and W_v to extract various levels of correlation between the input data.

With dominating performance of multi-headed attention over self-attention, many studies have tried to adapt multi-headed attention to the TSC domain. Transformers for classification usually employ a simple encoder structure consisting of attention and feed-forward layers. SAnD (Simply Attend and Diagnose) [132] architecture adopted a multi-head attention mechanism similar to a vanilla transformer [113] to classify clinical time series for the first time. The model uses both positional encoding and a dense interpolation embedding technique to incorporate temporal order into representation learning. In another study that classified vibration signals [133], time-frequency features such as Frequency Coefficients and Short Time Fourier Transformation (STFT) spectrums are used as input embeddings to the transformers. A multi-head attention-based model was applied to raw optical satellite time series classification using Gaussian Process Interpolation [134] embedding and outperformed convolution, and recurrent neural networks [135].

Gated Transformer Networks (GTN) [136] use two-tower multi-headed attention to capture the discriminative information from the input series. Also, they merged the output of two towers using a learnable matrix named gating. To enhance locality awareness of transformers for time series classification, flexible multi-head linear attention (FMLA) integrates deformable convolutional blocks and online knowledge distillation, as well as a random mask to reduce noise [137]. For each TSC dataset, AutoTransformer searches for the suitable network architecture using the neural architecture search (NAS) algorithm before feeding the output to the multi-headed attention blocks [138].

3.4.3 Attention based Self-supervised Models. Self-supervised learning is a type of learning where the model is trained on a dataset that has been automatically labeled rather than manually labeled by humans. This can be useful when manual labeling is difficult or expensive or when a large amount of available data can be used for training. In the context of time series classification or extrinsic regression, self-supervised learning can be applied by generating labels for the time series data automatically. For example, the model could be trained to predict the next time step in a sequence or to predict the values of a time series at a certain time step. These labels can then be used to train the model to learn useful features from the time series data that can help improve its classification performance.

Following the development of transformer-based self-supervised learning like BERT [114], many studies try to adopt the same structure for the time series classification [18, 116]. BErt-inspired Neural Data Representations (BENDER) [116] replaces an encoder designed for time series called wav2vec to leverage the same structure for time series data. BENDER shows that the pre-trained model can effectively model EEG sequences recorded with differing hardware if we have a massive amount of EEG data. Similarly, Voice-to-Series with Transformer-based Attention (V2Sa) uses a large-scale pre-trained speech processing model for downstream problems like time series classification [139]. In another study, a Transformer-based Framework (TST) was introduced to adopt vanilla transformers to the multivariate time series domain [18]. TST uses only the encoder part of a transformer and pretrains it with proportionally masked data in an unsupervised manner. Finally, the pre-trained models are fine-tuned in downstream tasks such as classification and regression.

Self-supervised learning can be a useful approach for time series classification in situations where there is a large amount of available data, and manual labeling is not feasible. However, the quality of the learned features and predictions may not be as good as those produced by supervised learning since the automatically generated labels may not accurately

Model	Year	Embedding	Attention
MuVAN [120]	2018	Bi-GRU	Self-attention
ChannelAtt [123]	2018	RNN	Self-attention
GeoMAN [124]	2018	LSTM	Self-attention
Multi-Stage-Att [125]	2020	LSTM	Self-attention
CT_CAM [126]	2020	FCN + Bi-GRU	Self-attention
CA-SFCN [17]	2020	FCN	Self-attention
RTFN [127]	2021	CNN + LSTM	Self-attention
LAXCAT [121]	2021	CNN	Self-attention
MACNN [122]	2021	Multi-scale CNN	Squeeze-and-Excitation
SAnD [132]	2018	Linear Embedding (Using 1D Conv)	Multi-Head
T2 [135]	2021	Gaussian Process Regression followed by 1D Conv	Multi-Head
GTN [136]	2021	Linear Embedding	Multi-Head
TRANS_tf [133]	2021	time-frequency features	Multi-Head
FMLA [137]	2022	Deformable CNN	Multi-Head
AutoTransformer [138]	2022	Multi-scale CNN + NAS	Multi-Head
BENDER [116]	2021	Wav2Vec 2.0 [141] + Self-Supervised	Multi-Head
TST [18]	2021	Linear Embedding + Self-Supervised	Multi-Head
TARNet [140]	2022	Linear Embedding + Self-Supervised	Multi-Head

Table 2. Summary of Attention-based models for time series classification and extrinsic regression

reflect the authentic underlying relationships in the data. TARNet [140] uses supervised attention score distribution, which is learned through classification or extrinsic regression tasks to mask the timestamps instead of randomly masking the input series.

4 APPLICATIONS - RECENT DEVELOPMENTS AND CHALLENGES

Time series classification and extrinsic regression are important techniques for analyzing and modeling time-dependent data. These methods have a wide range of applications, including human activity recognition, Earth observation, medical diagnoses, and many others. In this survey, we focus on the human activity recognition and Earth observation applications of time series classification and extrinsic regression and provide an overview of the latest developments and challenges in these areas.

4.1 Human Activity Recognition

Human activity recognition (HAR), is the identification or monitoring of human activity through the analysis of data collected by sensors or other instruments [142]. The recent growth of wearable technologies and the Internet of Things has resulted not only in the collection of large volumes of activity data [143], but also easy deployment of applications utilising this data to improve the safety and quality of human life [5, 142]. HAR is therefore an important field of research with applications including healthcare, fitness monitoring, smart homes [144], and assisted living [145].

Devices used to collect HAR data can be categorised as visual or sensor-based [4, 5]. Sensor-based devices can be further categorised as object sensors (for example RFIDs embedded into objects), ambient sensors (motion sensors, WiFi or Bluetooth devices in fixed locations) and wearable sensors [4], including smartphones [3]. However, the majority of

HAR studies use data from wearable sensors or visual devices [142]. Additionally, human activity recognition from visual device data requires the use of computer vision techniques and is therefore out of scope for this review. Accordingly, this section reviews wearable sensor-based methods of HAR. For reviews of vision-based HAR, refer to Kong and Fu [146] or Zhang et al. [147].

The main sensors used in wearable devices are accelerometers, gyroscopes and magnetic sensors [148], which each collect three-dimensional spatial data over time. Inertial measurement units (IMUs) are wearable devices that combine all three sensors in one unit [149, 150]. Several IMUs located on different parts of the body are typically used to collect data for wearable device studies [151, 152]. To create a dataset suitable for HAR modelling, the sensor data is split into (usually equally size) time windows [153]. The task is then to learn a function that maps the multi-variate sensor data for each time window to a set of activities. Thus, the data forms multi-variate time series and suited to time series classification methods.

Given the broad scope of our survey, this section necessarily only provides a brief overview of the studies using deep learning for HAR. However, there are several surveys that provide a more in-depth review of machine learning and deep learning for HAR. Lara and Labrador [153] provide a comprehensive introduction to HAR, including machine learning methods used and the principal issues and challenges. Both Nweke et al. [3] and Wang et al. [4] provide a summary of deep learning methods, highlighting their advantages and limitations. Chen et al. [5] discuss challenges in HAR and the appropriate deep learning methods for addressing each challenge. They also provide a comprehensive list of publicly-available HAR datasets. Gu et al. [154] focus on deep learning methods, reviewing preprocessing and evaluation techniques as well as the deep learning models.

The deep learning methods used for HAR include both CNNs and RNNs, as well as hybrid CNN-RNN models. While some of the models include an attention module, we did not find any studies proposing a full attention or transformer model. A summary of the studies reviewed and the type of model built is provided in table 3. Hammerla et al. [155] compared several deep learning model for HAR, include three LSTM variants, a CNN model, and DNN model. They found a bi-directional LSTM performed best on naturalistic datasets where long-term effects are important. However, they found some applications need to focus on short-term movement patterns and suggested CNNs are more appropriate for these applications. Thus, research across all model types is beneficial for the on-going development of models for HAR applications.

Many of the papers reviewed in this section used commonly available datasets to build and evaluate their models. A summary of the most commonly used datasets is provided in the .1.1 of the .1.

4.1.1 Convolutional neural networks. One of the most common types of convolutional kernels for HAR is the $k \times 1$ kernel. This kernel convolves k time steps together, moving along each time series in the input features in turn [177], so while weights are shared between the input features, there is no mixing between the features (Fig. 7). The outputs from the final convolutional layer are flattened and processed by fully-connected layers before the final classification is made. Ronao et al. [159] performed a comprehensive evaluation of CNN models for HAR, evaluating the effect of changing number of layers, filters and filter sizes used. The input data was collected from smartphone accelerometer and gyroscope sensors. Ignatov [163] used a one-layer CNN, and augmented the extracted features with statistical features before being passed to fully-connected layers. The architecture was effective with short time series (1 second) so useful for real time activity modelling.

One draw-back of the above method is that it forces weight-sharing across all the input features. This may not be optimal, especially when using data collected from multiple devices. In this case, using a separate CNN for each device

Model	Year	Embedding	Other features
Zeng et al. [156]	2014	CNN	
DCNN [157]	2015	CNN	Discrete Fourier Transform
Yang et al. [158]	2015	CNN	
DeepConvLSTM [148]	2016	CNN, LSTM	
Hammerla et al. [155]	2016	CNN, LSTM	Bi-directional
Ronao et al. [159]	2016	CNN	
Guan and Plötz [160]	2017	LSTM	Ensemble
Lee et al. [161]	2017	CNN	
Murad and Pyun [162]	2017	LSTM	Uni- & bi-directional
Ignatov [163]	2018	CNN	Statistical features
Moya Rueda et al. [164]	2018	CNN	
Yao et al. [165]	2018	CNN	Fully convolutional
Zeng et al. [166]	2018	LSTM	2 attention layers
AttnSense [167]	2019	CNN, GRU	Fast Fourier Transform, 2 attention layers
InnoHAR [168]	2019	CNN, GRU	Inception
Zhang et al. [169]	2020	CNN	Attention
Challa et al. [170]	2021	CNN, LSTM	Bi-directional
CNN-biGRU [171]	2021	CNN, GRU	Bi-directional
DEBONAIR [172]	2021	ConvLSTM	
Mekruksavanich and Jitpattanakul [173]	2021	CNN, LSTM	
Mekruksavanich and Jitpattanakul [174]	2021	CNN, LSTM	Ensemble
Nafea et al. [175]	2021	CNN, LSTM	Bi-directional
Singh et al. [176]	2021	CNN, LSTM	Attention
Wang et al. [177]	2022	CNN	
Xu et al. [178]	2022	CNN, Resnet	Deformable convolutions

Table 3. Summary of HAR deep learning models

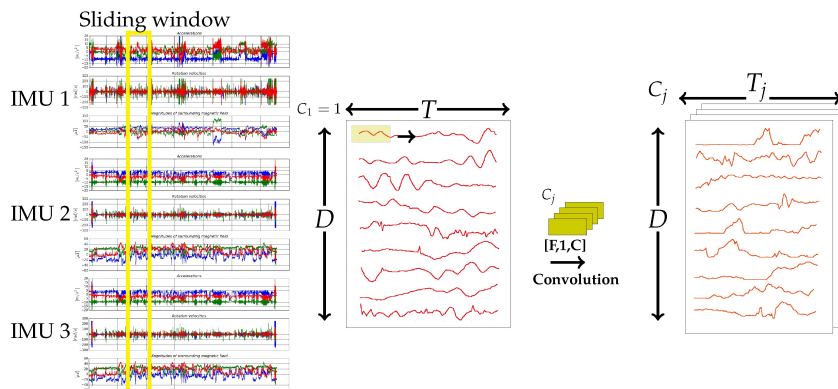


Fig. 7. A typical convolution for HAR modelling with data from IMUs. The kernel is size $F \times 1$ and convolves along each time series in turn. Image credit: Moya Rueda et al. [164, Figure 1], CC BY 4.0.

[164] allows independent weighting of the features. Similarly, as each sensor is typically tri-axial, a separate CNN can be used for each axis [156, 169]. The features extracted by each CNN are then concatenated and processed either by fully-connected layers [156] or an attention head [169].

While the above two methods are the most common, other studies have proposed alternative CNNs for HAR. DCNN [157] pre-processes the sensor data using a Discrete Fourier Transform to convert IMU data to frequency signals, then uses two-dimensional convolutions to extract combined temporal and frequency features. Lee et al. [161] pre-processed the tri-axial accelerometer data to a magnitude vector, which was then processed in parallel by CNNs with varying kernel sizes, extracting features at different scales. Xu et al. [178] used deformable convolutions [179] in both a 2D-CNN and a ResNet model and found these models performed better than their non-deformable counterparts. Yao et al. [165] proposed a fully convolutional model using two-dimensional temporal and feature convolutions. Their model has two advantages as (1) it handles arbitrary length input sequences and (2) it makes a prediction for each timestep, which avoids the need to pre-process the data into windows and can detect transitions between activities.

4.1.2 Recurrent neural networks. Several long short-term memory (LSTM) models have been proposed for HAR. Murad and Pyun [162] designed and compared three multi-layered LSTMs, a uni-directional LSTM, a bi-directional LSTM, and a “cascading” LSTM, which has a bi-directional first layer, followed by uni-directional layers. In each case the output from all time steps is used as input to the classification layer. Zeng et al. [166] added two attention layers to an LSTM, a sensor attention layer before the LSTM and a temporal attention layer after the LSTM. They include a regularisation term they called “continuous attention” to smooth the transition between attention weights. Guan and Plötz [160] created an ensemble of LSTM models by saving the models at every training epoch, then selecting the best “M” models based on validation set results, thus aiming to reduce model variance.

4.1.3 Hybrid models. Many recent studies have focussed on hybrid models, combining both CNNs and RNNs. DeepConvLSTM [148] comprises four temporal convolutional layers followed by two LSTM layers, which the authors found to perform better than an equivalent CNN (replacing the LSTM layers with fully-connected layers). As the LSTM layers have fewer parameters than fully-connected layers, the DeepConvLSTM model was also much smaller. Singh et al. [176] used a CNN to encode the spatial data (i.e. the sensor readings at each timestamp) followed by a single LSTM layer to encode the temporal data, then a self-attention layer to weight the time steps. They found this model performed better than an equivalent model using temporal convolutions in the CNN layers. Challa et al. [170] proposed using three 1D-CNNs with different kernel sizes in parallel, followed by 2 bi-directional LSTM layers and a fully-connected layer. Nafea et al. [175] also used 1D-CNNs with different kernel sizes and bi-directional LSTMs. However, they used separate branches for the CNNs and LSTMs, merging the features extracted in each branch for the final fully connected layer. Mekruksavanich and Jitpattanakul [173] compared a 4-layer CNN-LSTM model with a smaller CNN-LSTM model and LSTM models, finding the extra convolutional layers improved performance over the smaller models. DEBONAIR [172] is another multi-layered model. It uses parallel 1D-CNNs, each having different kernel, filter, and pooling sizes to extract different types of features associated with different types of activity. These are followed by a combined 1D-CNN, then two LSTM layers. Mekruksavanich and Jitpattanakul [174] ensembled four different models: a CNN, an LSTM, a CNN-LSTM, and a ConvLSTM model. They aimed to produce a model for biometric user identification that could not only identify the activity being performed, but also the participant performing the activity.

A few hybrid models use GRUs instead of LSTMs. InnoHAR [168] is a modified DeepConvLSTM [148], replacing the four CNN layers with inception layers and the two LSTM layers with GRU layers. The authors found this inception model performed better than both the original DeepConvLSTM model and a straight CNN model [158]. AttnSense [167] uses a Fast Fourier transform to generate frequency features which are then convolved separately for each time step. Attention layers are used to weight the extracted frequency features. These are then passed through a GRU with temporal attention to extract temporal features. CNN-BiGRU [171] uses a CNN layer to extract spatial features from the

sensor data, then one or more GRU layers extract temporal features. The final section of the model is a fully-connected module consisting of one or more hidden layers and a softmax output layer.

4.2 Satellite Earth Observation

Ever since NASA launched the first Landsat satellite in 1972 [180], Earth-observing satellites have been recording images of the Earth’s surface, providing 50 years of continuous Earth observation (EO) data that can be used to estimate environmental variables informing us about the state of the Earth. Instruments on board the satellites record reflected or emitted electromagnetic radiation from the Earth’s surface and vegetation [181]. The main modalities used for SITS analysis are multispectral spectrometers and spectroradiometers, which observe the visible and infrared (IR) frequencies and Synthetic Aperture Radar (SAR) systems which emit a microwave signal and measure the backscatter. A list of the main satellites and instruments used in the studies reviewed is provided in the .1.2 of the .1.

Raw data collected by satellite instruments needs to be pre-processed before being used in machine learning. This is frequently done by the data providers to produce analysis ready datasets (ARD). With the increasing availability of compatible ARD datasets from sources such as Google Earth Engine [182] and various data cubes [183, 184], models combining data from multiple data sources (multi-modal) are becoming more common. These data sources make it straightforward to obtain data that are co-registered (spatially aligned and with the same resolution and projection), thus avoiding the need for complex pre-processing.

SITS data can be processed either (1) as two-dimensional temporal and spectral data, processing each pixel independently and ignoring the spatial dimensions, or (2) as four-dimensional data, including the two spatial dimensions, thus models extract spatio-temporal features. This latter method allows estimates to be made at pixel, patch, or object level, however it requires either more complex models, or spatial features to be extracted in a pre-processing step. Feature extraction can be as simple as extracting the mean value for each band. However, both clustering (TASSEL, [185]), and neural-network based methods, such as the Pixel-Set Encoder [186] have been used for more complex feature extraction.

The most common use of SITS deep learning is for the classification of the Earth’s surface by land cover and agricultural land by crop types. The classes used can range from very broad land cover categories (such as forest, grasslands, agriculture) through to specific crops types. Other classification tasks include identifying specific features, such as sink-holes [187], burnt areas [188], flooded areas [189], roads [190], deforestation [191], vegetation quality [192] and forest understory and litter types [193].

Extrinsic regression tasks are not as common as classification tasks, but several recent studies have investigated methods of estimating water content in vegetation, as measured by the variable Live Fuel Moisture Content (LFMC) [194–197]. Other regression tasks include estimating the wood volume of forests [198] by using a hybrid CNN-MLP model combining a time series of Sentinel-2 images with a single LiDAR image and crop yield [199] which uses a hybrid of CNN and LSTM.

Many different approaches to learning from SITS data have been studied, with studies using all the main deep learning architectures, adapting them for multi-modal learning, and combining architectures in hybrid and ensemble models. The rest of this section reviews the architectures that have been used to model SITS data. A summary of these papers and architectures is provided in table 4.

4.2.1 Recurrent Neural Networks (RNNs). One of the first papers to use RNNs for land cover classification was Ienco et al. [216], who showed an LSTM model out-performed non deep learning methods such as Random Forest (RF) and Support Vector Machines (SVM). However, they also showed that the performance of both RF and SVM improves if

Model	Year	Embedding	Other features
Crop type classification			
TAN [200]	2019	2D-CNN & GRU	Attention – temporal
TGA [201]	2020	2D-CNN	Attention – squeeze and excitation
3D-CNN [202]	2018	3D-CNN	
DCM [203]	2020	LSTM	Self-attention
HierbiLSTM [204]	2022	LSTM	Self-attention
L-TAE [205]	2020	MLP	Attention – temporal
PSE-TAE [186, 206]	2020	MLP	Attention – temporal optionally Multi-modal
SITS-BERT [207]	2021		Pre-trained transformer
Land Cover classification			
1D-CNN [208]	2017	1D-CNN & MLP	Hybrid model
1D & 2D-CNNs [209]	2017	1D-CNN; 2D-CNN	Ensemble model
TempCNN [210]	2019	1D-CNN	
TASSEL [185]	2020	1D-CNN	Self-attention
TSI [211]	2021	1D-CNN; LSTM	Ensemble model
TWINNS [212]	2019	2D-CNN & GRU	Attention – temporal; Multi-modal
DuPLO [213]	2019	2D-CNN & GRU	Attention – temporal
Sequential RNN [214]	2018	2D-FCN & LSTM	Hybrid model
FG-UNET [215]	2019	UNet & 2D-CNN	Hybrid model
LSTM [216]	2017	LSTM	
HOb2sRNN [217]	2020	GRU	Attention – temporal
OD2RNN [218]	2019	GRU	Attention – temporal; Multi-modal
SITS-Former [219]	2022	3D-CNN	Pre-trained transformer
Other classification tasks			
Deforestation [191]	2022	U-Net & LSTM	Hybrid model
Flood detection [189]	2020	Resnet & GRU	Hybrid model
Forest understory [193]	2022	2D-CNN & LSTM	Ensemble model
Road detection [190]	2020	U-Net & convLSTM	Hybrid model
Vegetation quality [192]	2017	LSTM; GRU	
Extrinsic regression tasks			
TempCNN-LFMC [195]	2021	1D-CNN	
Multi-tempCNN [196]	2022	1D-CNN	Multi-modal, ensemble model
LFMC estimation [194]	2020	LSTM	Multi-modal
LFMC estimation [197]	2022	1D-CNN & LSTM	Multi-modal, hybrid, ensemble
MLDL-net [199]	2020	2D-CNN & LSTM	Hybrid model
SSTNN [220]	2021	3D-CNN & LSTM	Hybrid model
MMFVE [198]	2022	2D-CNN	Hybrid model

Table 4. Summary of SITS deep learning models

trained on features extracted by the LSTM model, and in some cases were more accurate than the straight LSTM model. Rao et al. [194] used an extrinsic regression LSTM model to estimate LFMC in the western CONUS.

More commonly, however, RNNs are combined with an attention layer to allow the model to focus on the most important time steps. The OD2RNN model [218], used separate GRU layers followed by attention layers to process Sentinel-1 and Sentinel-2 data, combining the features extracted by each source for the final fully-connected layers. HOb2sRNN [217] refined OD2RNN by using a hierarchy of land cover classifications; the model was pretrained using broad land cover classifications, then further trained using the finer-grained classifications. DCM [203] and HierbiLSTM [204] both use a bi-directional LSTM, processing the time series in both directions, followed by a self-attention

transformer for a pixel-level crop-mapping model. All these studies found adding the attention layers improved model performance over a straight GRU or LSTM model.

4.2.2 Convolutional Neural Networks (CNNs). While many authors have claimed that RNNs out-perform CNNs for land cover and crop type classification, most of these comparisons are to 2-dimensional CNNs (2D-CNN), that ignore the temporal ordering of SITS data [210]. However, other studies show using 1-dimensional CNNs (1D-CNNs) to extract temporal information or 3-dimensional CNNs (3D-CNNs) to extract spatio-temporal information are both effective methods of learning from SITS data.

TempCNN [210] consists of three 1D convolutional layers. The output from the final convolutional layer is passed through a fully-connected layer, then the final softmax classification layer. TASSEL [185], is an adaptation of TempCNN for OBIA classification, using TempCNN models to process features extracted from the objects, followed by an attention layer to weight the convolved features. TempCNN has also been adapted for extrinsic regression [195] and used for LPMC estimation [195–197].

2D-CNNs are mainly used to extract spatial or spatio-temporal features for both pixel and object classification. The model input is usually 4-dimensional and the data is convolved spatially, with two main methods used to handle the temporal dimension. In the first method, each time step is convolved separately and the extracted features are merged in later stages of the model [201]. In the second method, the time steps and channels are flattened to form a large multivariate image [198, 209]. FG-UNet [215] is a fully-convolutional model that combines both the above methods, first grouping time steps by threes to produce images with 30 channels (10 spectral \times 3 temporal), which are passed through both U-Net and 2D-CNN layers.

Ji et al. [202] used a three-dimensional CNN (3D-CNN) to convolve the spatial and temporal dimensions together, combining the strengths of 1D-CNN and 2D-CNNs. The study found a 3D-CNN crop classification model performed significantly better than the 2D-CNN, again showing the importance of the temporal features. Another study, SSTNN [220] obtained good results for crop yield prediction by using a 3D-CNN to convolve the spatial and spectral dimensions, extracting spatio-spectral features for each time step. These features were then processed by LSTM layers to perform the temporal modelling.

4.2.3 Transformer and Attention Models. As an alternative to including attention layers with a CNN or RNN, several studies have designed models that process temporal information using only attention layers. PSE-TAE [186] used a modified transformer called a temporal attention encoder (TAE) for crop mapping and found the TAE performed better than either a CNN or an RNN. L-TAE [205] replaced the TAE with a light-weight transformer which is both computationally efficient and more accurate than the full TAE. Ofori-Ampofo et al. [206] adapted the TAE model for multi-modal inputs, using Sentinel-1 and Sentinel-2 data for crop type mapping. Rußwurm and Körner [221] compared a self-attention model with RNN and CNN architectures. They found that this model was more robust to noise than either RNN or CNN and suggested self-attention is suitable for processing raw, cloud-affected satellite data.

Building on the success of pre-trained transformers for natural language processing (NLP) such as BERT [114], pre-trained transformers have been proposed for EO tasks [207]. Earth observation tasks are particularly suited for pre-trained models as large quantities of EO data are readily available, while labelled data can be difficult to obtain [222], especially in remote locations. SITS-BERT [207] is an adaptation of BERT [114] for pixel-based SITS classification. For the pretext task, random noise is added to the pixels, and the model is trained to identify and remove this noise. The pre-trained model is then further trained for required tasks such as crop type or land cover mapping. SITS-Former [219] modifies SITS-BERT for patch classification by using 3D-Conv layers to encode the spatial-spectral information, which

is then passed through the temporal attention layers. The pretext task used for SITS-Former is to predict randomly masked pixels.

4.2.4 Hybrid Models. A common use of hybrid models is to use a CNN to extract spatial features and an RNN to extract temporal features. Garnot et al. [223] compared a straight 2D-CNN model (thus ignoring the temporal aspect), a straight GRU model (thus ignoring the spatial aspect) and a combined 2D-CNN and GRU model (thus using both spatial and temporal information) and found the combined model gave the best results, demonstrating that both the spatial and temporal dimensions provide useful information for land cover mapping and crop classification. DuPLO [213] was one of the first models to exploit this method, running a CNN and ConvGRU model in parallel, then fusing the outputs using a fully-connected network for the final classifier. During training, an auxiliary classifier for each component was used to enhance the discriminative power. TWINNS [212] extended DuPLO to a multi-modal model, using time series of both Sentinel-1 (SAR) and Sentinel-2 (Optical) images. Each modality was processed by separate CNN and convGRU models, then the output features from all four models were fused for classification.

Other hybrid models include Li et al. [200], who used a CNN for spatial and spectral unification of Landsat-8 and Sentinel-2 images which were then processed by a GRU. MLDL-Net [199] is a 2D-CNN extrinsic regression model, using CNNs to extract time step features, which are then passed through an LSTM model to extract temporal features. Fully connected layers combine the feature sets to predict crop yield. Rußwurm and Körner [214] extracted temporal features first, using a bi-directional LSTM, then used a fully-convolutional 2D-CNN to incorporate spatial information and classify each pixel in the input patch.

4.2.5 Ensemble Models. One of the easiest ways to ensemble DL models is to train multiple homogeneous models, that vary only in the random weight initialisation [224]. Di Mauro et al. [208] ensembled 100 LULC models with different weight initialisations by averaging the softmax predictions. They found this produced a more stable and stronger classifier that outperformed the individual models. Multi-tempCNN [196], a model for LFMC estimation, is an ensemble of homogeneous models for extrinsic regression. The authors suggested that as an additional benefit, the variance of the individual model predictions can be used to obtain a measure of uncertainty of the estimates. TSI [211] also ensembled a set of homogeneous models, but instead of relying on random weight initialisation to introduce model diversity, the time series are segmented and models trained on each segment.

Other methods create ensembles of heterogeneous models. Kussul et al [209] compared ensembles of 1D-CNNs and 2D-CNNs models for land cover classification. Each model in the ensemble used a different number of filters, so finding different feature sets useful for classification. Xie et al. [197] ensembled three heterogeneous models – a TCN, an LSTM, and a hybrid TCN-LSTM model – for an extrinsic regression model to estimate LFMC. The ensembles were created using stacking [225]. The authors compared this method to boosting their TCN-LSTM model, using Adaboost [226] to create a three-member ensemble, and found that stacking a diverse set of models out-performed boosting.

4.2.6 EO Surveys and Reviews. This survey is one of very few that includes a section focusing specifically on deep learning TSC and TSER tasks using SITS data. However, there are other reviews that provide further information about related topics. Gomez et al. [227] is an older review highlighting the importance role of SITS data for land cover classification. Zhu et al. [228] reviewed the advances and challenges in DL for remote sensing, and the resources available that are potentially useful to help DL address some of the major challenges facing humanity. Ma et al. [229] studies the role of deep learning in Earth observation using remotely sensed data. It covers a broad range of tasks including image fusion, image segmentation and object-based analysis, as well as classification tasks. Yuan et al. [230] provide a review

of DL applications for remote sensing, comparing the role of DL versus physical modelling of environmental variables and highlighting challenges in DL for remote sensing that need to be addressed. Chaves et al. [231] reviewed recent research using Landsat 8 and/or Sentinel-2 data for land cover mapping. While not focused on SITS DL methods, the review notes the growing importance of these methods. Moskolai et al. [232] is a review of forecasting applications using DL with SITS data that provides an analysis of the main DL architectures that are relevant for classification as well as forecasting.

5 CONCLUSION

In conclusion, this survey paper has discussed a variety of deep network architectures for time series classification and extrinsic regression tasks, including multilayer perceptrons, convolutional neural networks, recurrent neural networks, and attention-based models. We have also highlighted refinements that have been made to improve the performance of these models on time series tasks. Additionally, we have discussed two critical applications of time series classification and regression, human activity recognition and satellite Earth observation. Overall, using deep network architectures and refinements has enabled significant progress in the field of time series classification and will continue to be essential for addressing a wide range of real-world problems. We hope this survey will stimulate further research using deep learning techniques for Time series classification and extrinsic regression.

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.1 Appendix

.1.1 *HAR Datasets.* Many of the studies reviewed in the subsection reviewing the use of deep learning for human activity recognition time series use publicly available datasets. Some of the most commonly used datasets are listed in table 5, together with the number of participants, the sensors used to collect the data, a description of the activities recorded, and references to the studies using each dataset. Larger lists of datasets are provided in [5, 143]. Common activity sets include activities of daily living (ADL) or basic activities (e.g. walking, running, sitting, standing, ascending/descending stairs. However, activities for more specialised events such as gait freezing in Parkinson’s Disease patients [233], falls [234], and manufacturing activities [235] are also collected.

Name	Partici- pants	Sensors	Activities/ Description	Used by
DAPHNet FoG [233]	10	3 accelerometers attached to the body	Detection of freezing of gait events in Parkinson’s Disease patients.	[155, 162, 166]
Opportunity challenge [151, 236]	4	5 on-body IMUs each with 3 sensors	A variety of activities of daily living.	[148, 156, 164, 177, 178] [155, 158, 160, 162, 165]
PAMAP2 [149, 237]	9	3 IMUs and heart rate monitor	18 basic and daily living activities.	[160, 164, 166, 177] [155, 167, 170, 172]
Skoda [235]	1	19 body-worn sensors	10 quality assurance activities from car production plant.	[148, 156, 162] [160, 166, 167]
UCI-HAR [238]	30	Smartphone accelerometer and gyroscope	6 basic activities.	[157, 159, 162, 163, 177] [170, 173–175]
UniMiB SHAR [234]	30	Smartphone accelerometers	Activities of daily living and falls.	[177, 178]
USC-HAD [150]	14	Motion node (accelerometer, gyroscope, and magnetometer) attached to hip	12 basic activities.	[157, 162, 174, 176, 178]
WISDM [239]	29	Smartphone accelerometer	6 basic activities.	[163, 169, 177, 178] [170, 175, 176]

Table 5. Commonly used human activity recognition datasets

.1.2 *Earth observation satellites and instruments.* Table 6 lists the main satellites and instruments used in the studies reviewed for this survey. The table lists references for each source, which provide more details about the data collected, plus a list of the studies using each source.

Agency	Satellite & Instruments	Type	Used by
NASA	Landsat-7 ETM+ [240]	Optical	[203, 211]
NASA	Landsat-8 OLI [240]	Optical	[200, 201, 203, 209, 211], [191, 194, 197, 208]
NASA	Terra/Aqua MODIS [241]	Optical	[195–197, 199, 220]
ESA	Sentinel-1A/1B	Microwave	[194, 197, 206, 209, 212, 217],
	SAR-C [242]	SAR	[187–189, 192, 218]
ESA	Sentinel-2A/2B MSI [242]	Optical	[189, 191, 200, 201, 206, 212, 218], [185, 186, 204, 205, 207, 213, 223], [190, 193, 198, 214, 215, 219, 221]
CNES (France)	Pléiades-1A/1B HiRI [243]	Optical	[216]
NSPO (Taiwan)	Formosat-2 RSI [244]	Optical	[210]
CRESDA (China)	Gaofen-1/2 MUX, PAN, WFV [245, 246]	Optical	[202]

Table 6. Earth Observation satellites and instruments collecting the data used in the studies reviewed.