

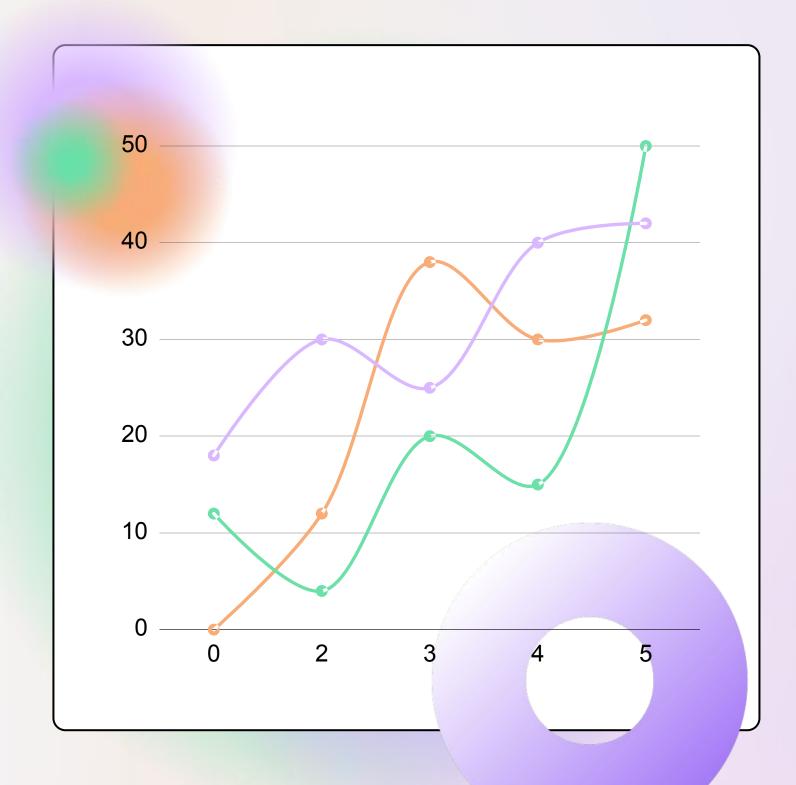
Time Series Classification through Deep Learning Techniques



A Comprehensive Exploration

Agenda

3	Introduction
4	Understanding Classification & Time Series
5	Preprocessing
6	Deep Learning Techniques for Time Series Classification
7	When , Why for each model
8	Case Studies and Applications
10	Conclusion: Recent Advancements and Challenges



Introduction

- Time series data—sequential data points.
- Importance of Time Series Classification.
- The Challenge of Complex Time Series Data,
 Why timeseries.

Classification

Binary	MultiClass	MultiLabel
Sorting things into two groups, like deciding if an email is spam or not, or if a loan will be approved or denied.	Sorting things into more than two groups, like recognizing numbers 0 to 9 from handwriting, or identifying different types of animals in pictures.	Assigning multiple labels to things, like tagging a photo with both "beach" and "sunset," or categorizing articles with topics like "science," "travel," and "food."

Timeseries

OVERIALE Series:

It's a sequence of numbers recorded at different times, showing how one thing changes over time.

Multivariate Time Series:

Instead of just one thing changing, you're keeping tabs on how multiple things change over time.

Examples:

- Imagine watching the temperature rise and fall throughout the day – that's an univariate time series!
- Picture monitoring not only the temperature but also the humidity and wind speed throughout the day – that's a multivariate time series!

The Challenge of Complex Time Series Data

- Variable-Length Sequences
- Temporal Dependencies
- Feature Extraction
- Class Imbalance
- Alignment and Synchronization
- Noise and Variability
- Multi-Dimensional Data
- Real-time Processing

- Model Complexity
- Generalization
- Transfer Learning
- Model Evaluation
- Labeling and Annotation
- Data Preprocessing
- Interpretable Results



Despite the challenges associated with time series data, it is still a valuable tool for many businesses and organizations. Here are some of the reasons why we use time series data:

- To predict future trends.
- To optimize operations.
- To make better decisions

Data Preprocessing for time series classification

Data cleaning Data transformation Data imputation Feature selection

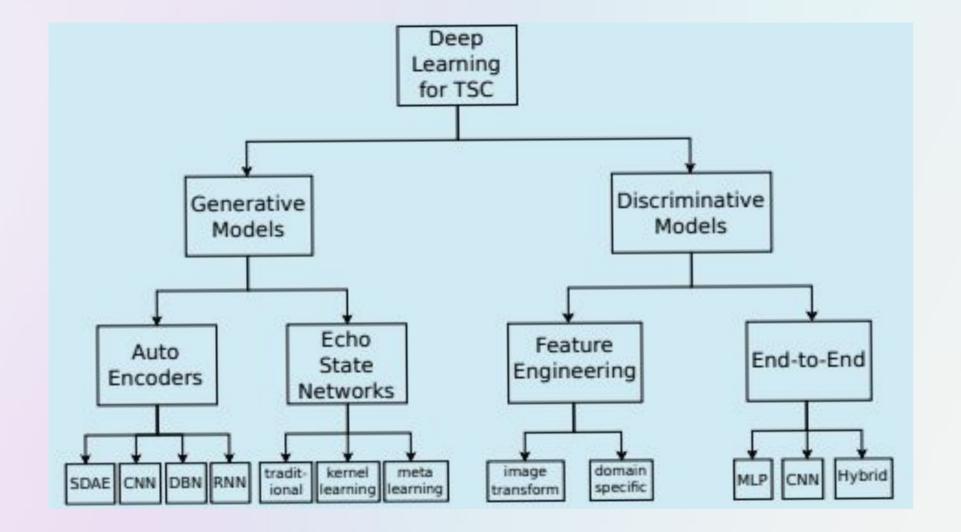
Removing errors, outliers, and missing values from the data.

Converting the data into a format that is suitable for time series analysis

Filling in missing values in the data

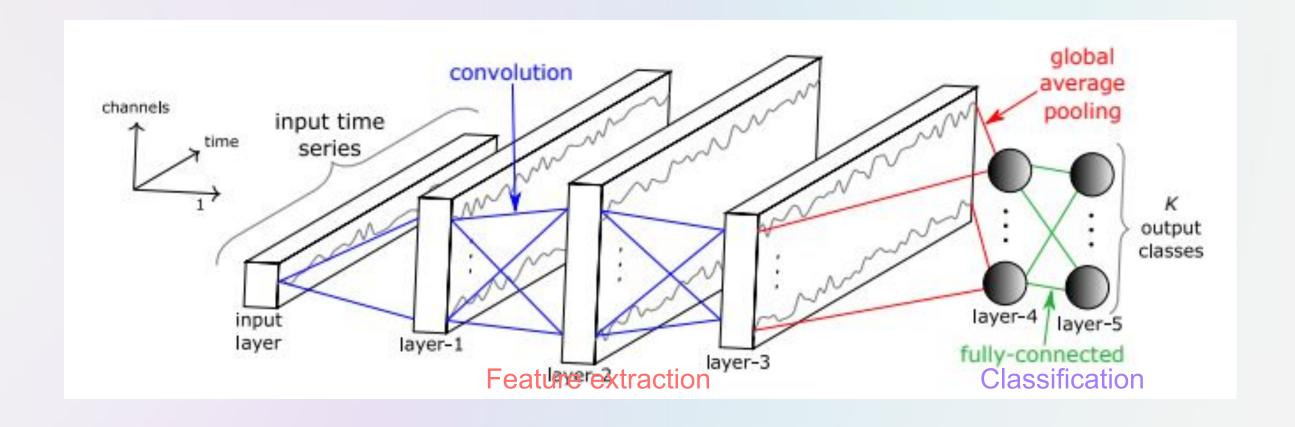
Selecting the most important features for time series analysis

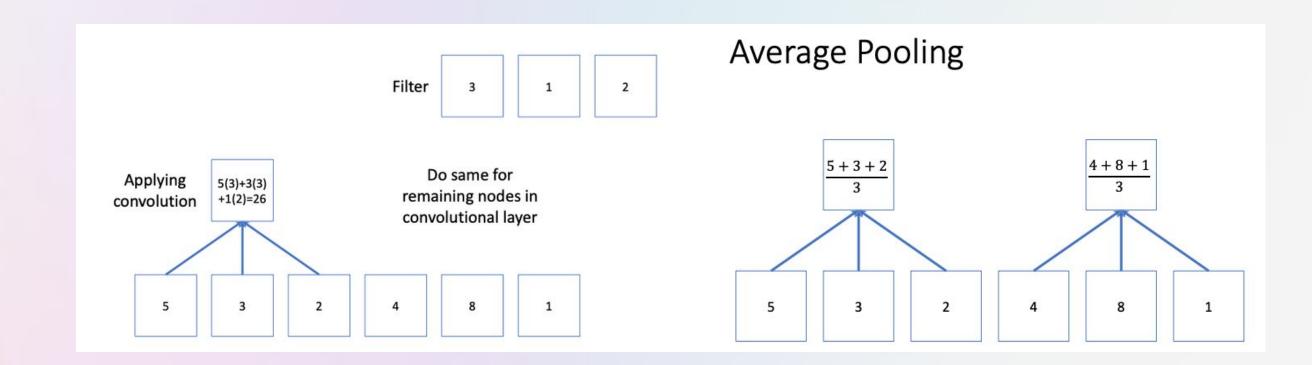
for time series classification



for time series classification

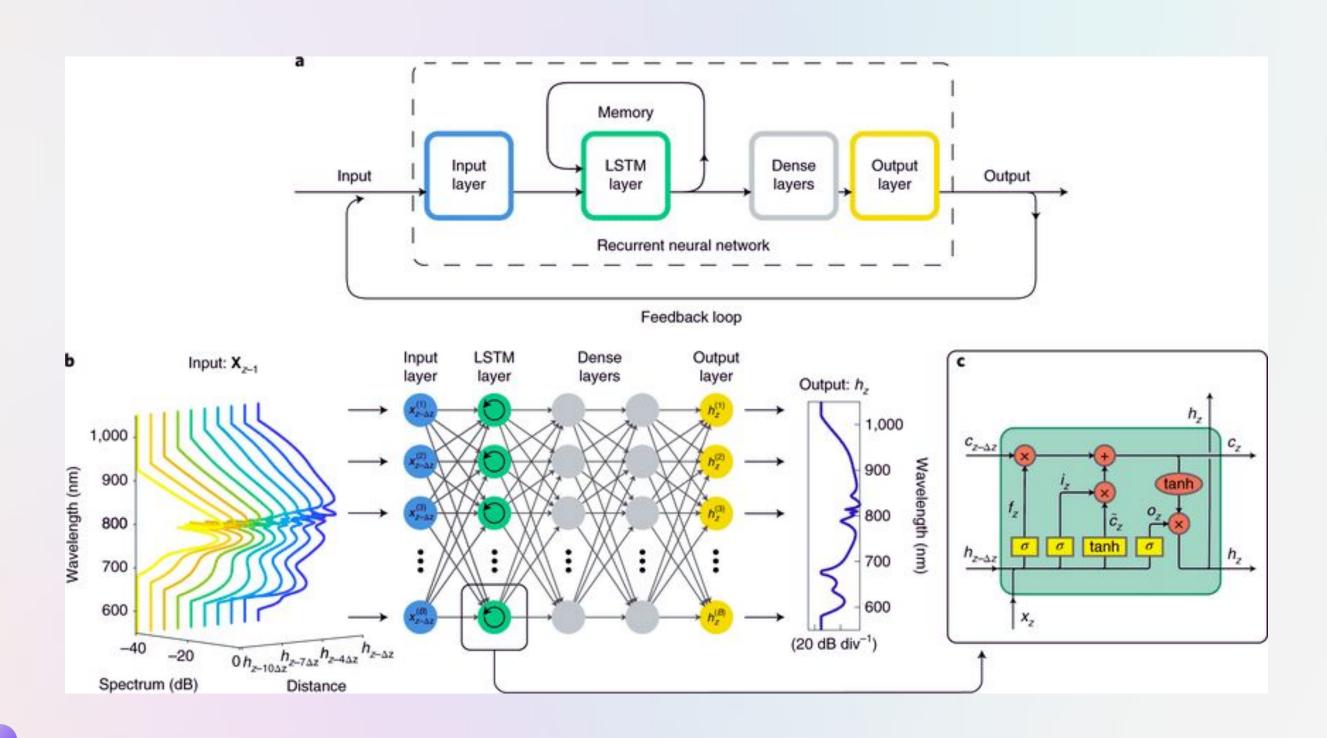
Convolutional neural networks (CNNs)





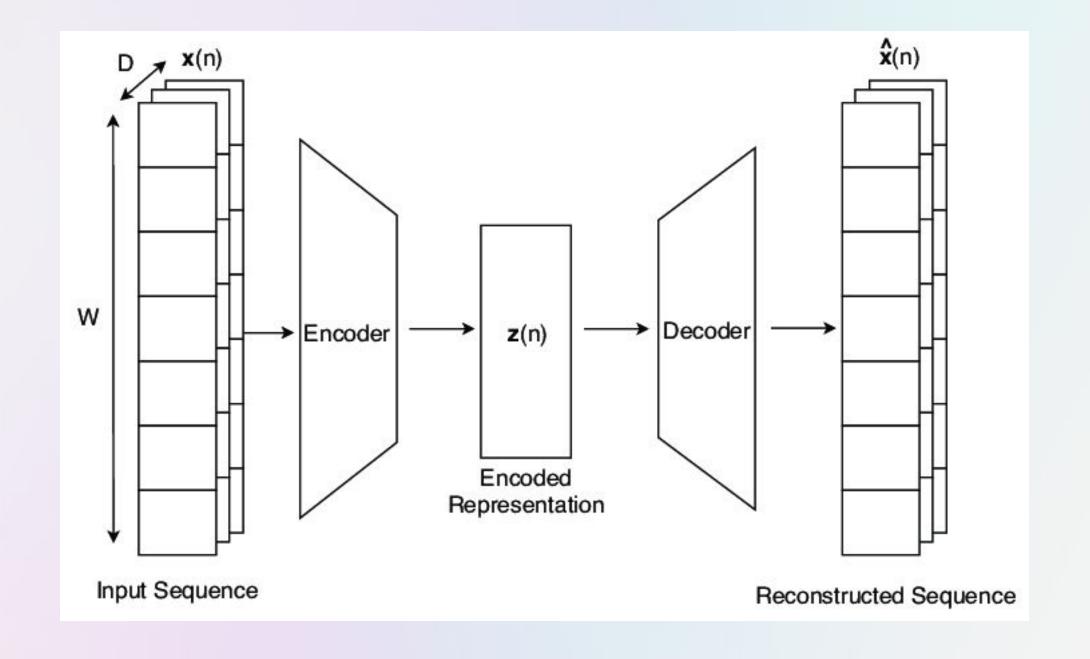
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Recurrent neural networks (RNNs)



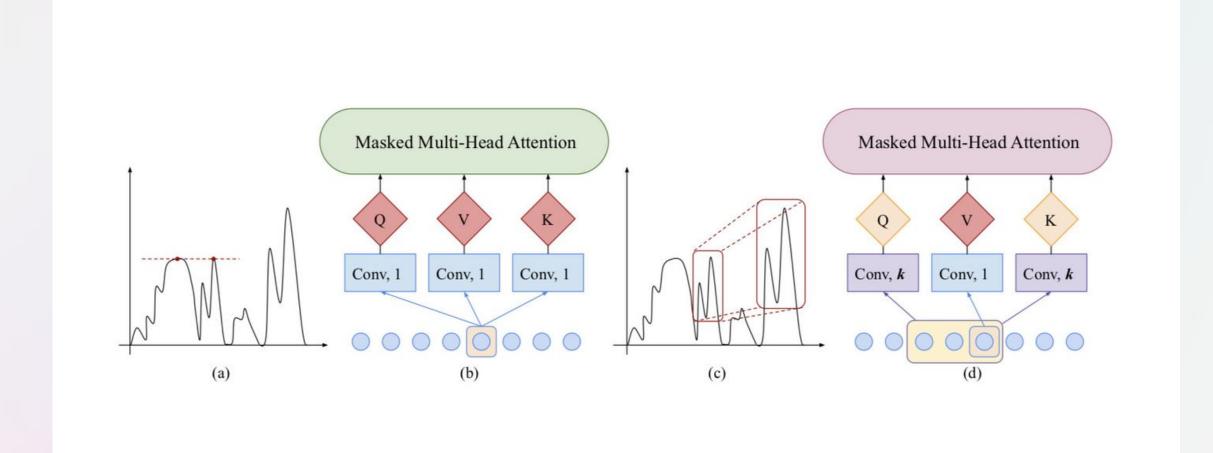
for time series classification

Autoencoders



for time series classification

Transformers



When, Why

for time series classification

Architecture	When to use	Why
Convolutional neural networks (CNNs)	When the time series data has a spatial or temporal dimension, such as images or audio recordings.	CNNs are well-suited for extracting features from data that has a spatial or temporal dimension. They can be used to extract features such as trends, seasonality, and patterns.
Recurrent neural networks (RNNs)	When the time series data is sequential, such as financial data or sensor data.	RNNs are specifically designed to process sequential data. They can be used to capture long-term dependencies in time series data, which can be important for classification tasks.
Transformers	When the time series data is long and has complex dependencies.	Transformers are a powerful type of neural network that can learn long-range dependencies. They can be beneficial for classification tasks on long and complex time series data.
Bidirectional RNNs	When it is important to capture both past and future information from the time series data.	Bidirectional RNNs combine a forward RNN with a backward RNN. This allows them to capture both past and future information from the time series data.
Convolutional-recurrent neural networks (CRNNs)	When it is important to capture both spatial and temporal features from the time series data.	CRNNs combine CNNs with RNNs. This allows them to capture both spatial and temporal features from the time series data.
Graph neural networks (GNNs)	When the time series data has a graph structure.	GNNs are specifically designed for processing data that has a graph structure. They can be used to learn relationships between different time series data points.

Case Studies and Applications

- Fraud detection: Time series classification can be used to detect fraudulent transactions based on their financial data. This can help to protect financial institutions from losses.
- Risk assessment: Time series classification can be used to assess the risk of financial instruments based on their historical performance data. This can help investors to make informed decisions.
- Disease diagnosis: Time series classification can be used to diagnose diseases based on patient data such as their vital signs, medical history, and lab results. This can help to improve the accuracy of diagnoses and reduce the time to treatment.
- Patient monitoring: Time series classification can be used to monitor patients for signs of deterioration based on their vital signs and other medical data. This can help to identify problems early on and prevent complications.
- Asset management: Time series classification can be used to monitor the health of energy assets such as power plants and pipelines. This can help to prevent costly outages and improve the efficiency of energy production.
- Route optimization: Time series classification can be used to optimize the routing of vehicles based on real-time traffic conditions and delivery schedules. This can help to reduce travel time and improve fuel efficiency.