Mutual and Common Utility between data representation variations

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Abstract: Providing an outline of a method that improves the accuracy of forecasting or classification by recognizing transformations in time series and image data systems is the objective of this study. The technique provides an outline of the method. Within the scope of this work, a quick review of identifying transformations is provided, as well as a discussion of pre-processing transformation approaches that emphasize essential components. Furthermore, it consists of necessary components. Even though the data is so complicated, the study shows how useful it is to use visual representations and computer vision techniques. By utilizing this strategy, individuals can acquire a more profound appreciation of the reasoning behind the results of CNN predictions. This is because the method makes it simpler to visualize the essential components that are required for accurate prediction or classification.

Keywords: Predictive modelling, Artificial intelligence, Time series, machine learning, deep Learning, CNN.

1. Introduction

The core notion of receiving knowledge with least effort is based on expertise in mathematical computation. The study of mathematics allows us to understand the evolution of variables over time using simple geometric curves, making it logistically and economically possible. This fundamental type of geometry is known as a 'time series'. Silva et al [1] introduced a brief definition of time series. The field of time series modelling has experienced substantial growth due to its wide-ranging applications in several disciplines. Time series data appear extensively in various scientific domains and industrial applications. Some important real-life applications of time series modelling and prediction are: biometric authentication such as on line signature verification [2], Electrocardiogram (ECG) analysis in medicine, stocks prediction in finance, energy usage prediction in power grids, human activity recognition [3], and weather prediction in meteorology and solar activity prediction in space weather.

Thus, for meaningful use of time series data, it is needed to be analysed. Time series analysis allows individuals to comprehend patterns in past data and generate predictions for both the near and distant future. It aids decision-makers in making predictions, foreseeing future trends, reducing risks, and making well-informed and impartial judgments [4]. Traditional time series classification and forecasting techniques, based on statistical probability models, have proven effective. However, the rise of big data has posed a new challenge. The high-volume and high-velocity data exhibit non-linear and different patterns. Machine learning and artificial intelligence are used to analyse complicated patterns and develop models. Deep architectures have lately shown state-of- the-art performance in several different domains and many researchers have proposed some new pre-processing representation transformation technologies to maximize model accuracy and overcome the problem of poor performance in many applications to maintain sensitivity of changes between categories. The input data in these advanced disciplines exhibit temporal correlation (1-D time series), spatial correlation (images), or can be modified to possess such characteristics, for example, in the case of sound, through the utilization of time-frequency analysis. This adjustment has significantly improved outputs accuracy and capabilities. This research investigates the utilization of intermediate representation learning methods and their potential for applications in prediction and classification. Figure 1 shows a rough outline of how the work is organized.

Problem definition

Transforming data instead of modifying the model might be a better way to improve the model's accuracy, according to certain studies [5-7]. This can be justified by the fact that modifications can alter statistical characteristics of the data; for instance, differencing helps time series to be stabilized. Effective Mutual and Common Utility between Time series, symbols, Graphs, and images is the basis for our study motivations. Nakano, Kotaro & Basabi [8] examined how time series data representation strategies improve classification accuracy while remaining cost-effective and easy to understand

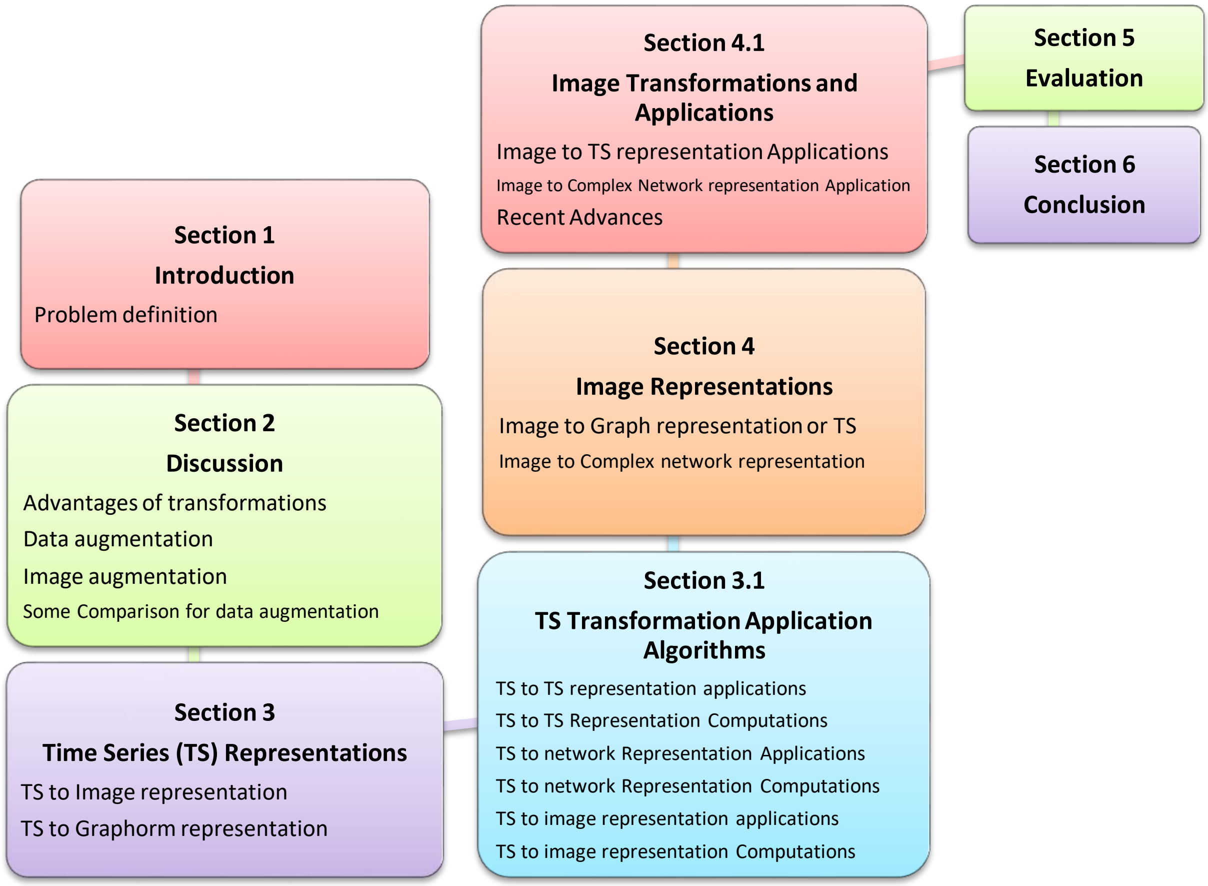


Figure 1. The exact plan of the structure is revealed in this quick review.

2. Discussion

Theories and models possess significant utility yet are not without limitations. They are regarded as direct modeling methods that are inapplicable for modeling various data kinds. In order to make direct methods more accurate, we need new methods that aren't only direct. Therefore, we can employ indirect approaches, namely transformations. A time series can be represented graphically by the vision algorithm. The graph inherits time series features as well. Numerous academics have analyzed the time series using the network, as indicated by the vision graph. Time-series image translation translates time-series data into visual formats, such as images. It is an essential process within the context. This technique diminishes data dimensionality by condensing voluminous data into a concise visual representation, enhancing its efficacy in identifying essential features and patterns from time-series data.

In contrast; image can be transferred to another type; since raw data is available in a number of formats, such as time series and images. Transforming between the forms has been popular among researchers who want to use the unique features of each type to make the model more accurate. The tonal distribution in a digital image can be represented graphically by an image histogram, a particular kind of histogram. The graph illustrates the pixel count corresponding to each tonal value. Figure 2 shows an image histogram.

Advantages of transformations

The following are some of the benefits that come with representing data: One of the benefits is that it is simpler to visualize and understand intricate patterns or trends. ii) It offers graphical representations of temporal data, which enables intuitive interpretation and pattern recognition with ease. iii) Transforming multiple-dimensional time series data can be a good way to lower the number of dimensions while keeping the temporal dependencies. This can make research go more quickly and give you more useful information. iv. Deep learning techniques can be used to successfully look at these data in image-based analysis for uses like identifying patterns or keeping an eye on healthcare.

(a) (b)

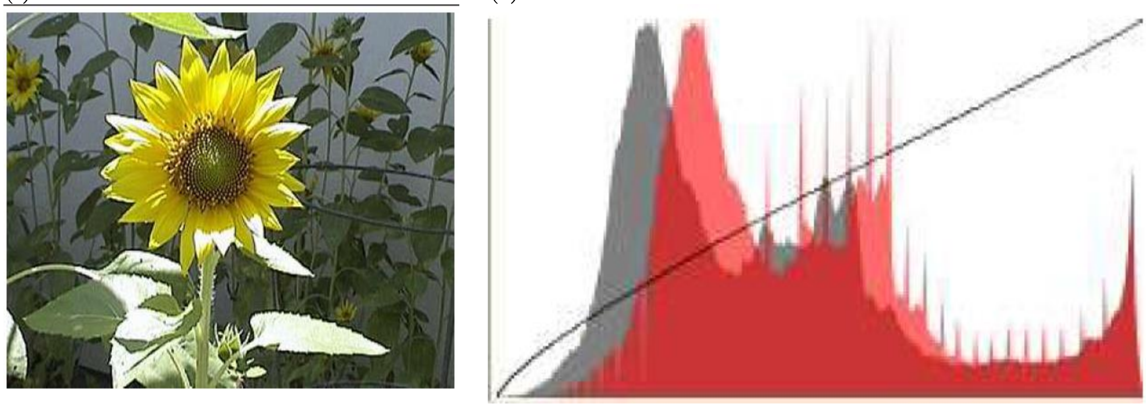


Figure 2. (a) Original image; (b) histogram of the same image

Data augmentation

Data augmentation in data analysis refers to approaches for increasing the amount of data by adding significantly changed copies of previously existing data or newly created synthetic data from existing data. It serves as a regularizer and decreases overfitting in machine learning model training.

Image augmentation

In the process of training a model, image augmentation is a technique that involves making modifications to data that has been collected in the past in order to generate fresh data that may be utilized in subsequent training. To put it another way, it is an overstatement of the quantity of the dataset that is now available for use in the process of training a deep learning model.

Traditional transformations like cropping, rotating, and flipping input images are a very common and accepted way to add to image data. This is one of the best ways to add data. In modern practice, data enrichment is used to make training data more diverse without actually collecting new data. It has been widely used as an effective way to improve generalization, especially when training deep neural networks. Certain data-augmented strategies have been proposed by researchers, which have, in fact, resulted in an improvement in accuracy.

Some Comparison for data augmentation

The tests in [9] demonstrate that the combination of three basic time domain approaches (permutation, rotation, and time warping) outperforms a single method in time series classification.

Also, the findings in [10] indicate significant performance enhancement in a time series classification task through the application of a deep neural network that integrates four data augmentation techniques: jittering, scaling, rotation, and time warping. However, when taking into account multiple data augmentation techniques, merging them directly could produce a large quantity of data and might not be the most efficient or effective way to improve performance.

Recently, Rand Augment [11] was proposed as an effective method for combining augmentations in image classification and object detection. Rand Augment utilizes two interpretable hyperparameters: N, which denotes the number of augmentation methods to combine, and M, representing the magnitude for all augmentation methods. Each augmentation is randomly selected from a set of K=14 available methods.

Temiz, H. [12] experimentally examined the impact of data enrichment on the performance of deep networks in the super-resolution problem. Six fundamental image transformations were employed in the enrichment procedures. Two deep network models were trained using variants of the ILSVRC2012 dataset, which were enhanced by six image transformation processes. He stated that for a single image change, enrichment with a 90-degree rotation yields optimal results. The models' most unsuccessful outcome was achieved when they were trained on enriched data that was generated by a reverse upside-down operation. The models achieve the highest ratings when they are trained with a combination of all translations.

3. Time Series (TS) Representations

Time series representation approaches can be in three types:

Pseudo Time Series; Time Series (TS) to time series transformations.
Image.
Graphorm. Figure 3 shows the three different representation schemes.

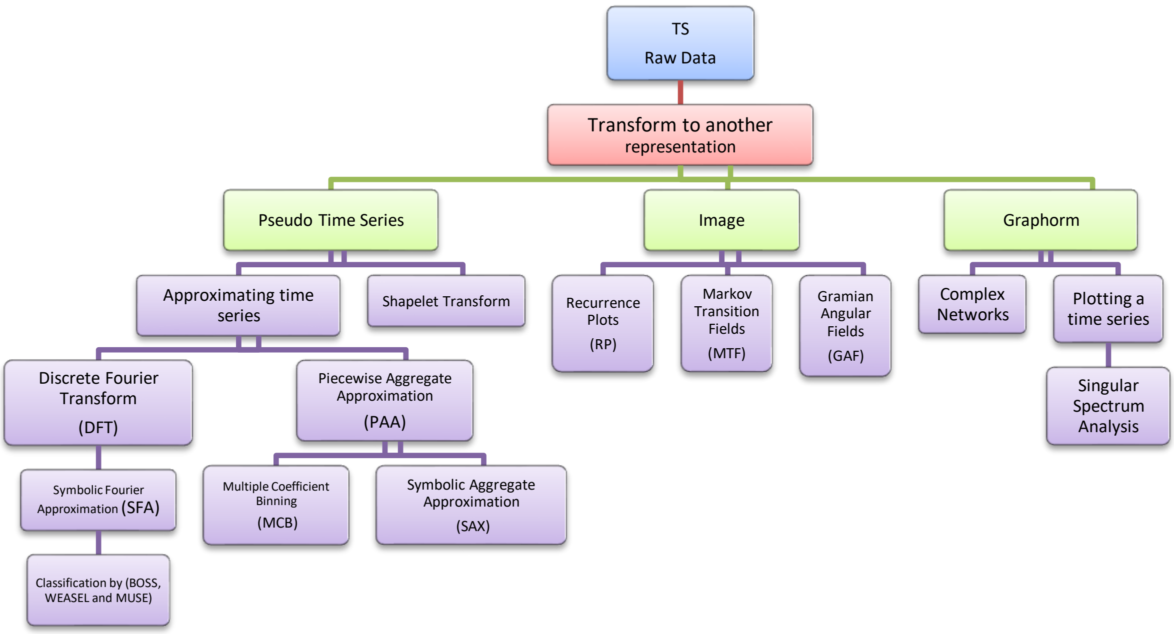


Figure 3: Types of commonly used representations: Pseudo Time Series, Synthesis Image, and Graphorm.

Pseudo Time Series representation

There are different techniques for approximating Time series:

The Shape let Transform algorithm extracts shape lets from a time series data collection and calculates the distances between them and the time series. A shape let is a subset of a time series, consisting of values from consecutive time points. The distance between a shape let and a time series is defined as the shortest distance between this shape let and all the shape lets of the same length retrieved from this time series. The most discriminatory shape lets are chosen.

The Discrete Fourier Transform transforms a signal of size n into a vector of complex Fourier coefficients. For float signals, the transformation can be made bijective. The first Fourier coefficients represent the trend, while the last coefficients represent noise.

Time series with high sample rates can be noisy. Piecewise Aggregate Approximation (PAA), which takes the mean over back-to-back points, reduces noise. This preserves the time series trend by reducing points and noise.
After estimating the time series, we can use these strategies:

The Symbolic Aggregate Approximation (SAX) approach separates continuous time series into intervals and then converts each interval (a sequence of floats) into a sequence of symbols, usually letters.

Multiple Coefficient Binning (MCB) algorithm converts each time point of all-time series (a sequence of floats) into a sequence of symbols, usually letters, by binning continuous time series into intervals. In contrast to SAX, which bins each time series independently, MCB bins each time point separately.

As a common practice, time series are frequently converted into sequences of symbols. After then, bag-of-words methods are utilized in order to extract features from these sequences.

TS to Image representation

An image can be interpreted as either a spatial or two-dimensional signal [13]. The process of creating new images from an existing dataset is known synthesis. Synthesis images for the time series are below:
A Gramian angular field is a visual representation derived from a time series, which depicts the temporal correlation between each pair of values in the time series. There are two available methods: Gramian angular summation field and Gramian angular difference field.
A Markov transition field is an image derived from a time series, which depicts a grid of transition probabilities for a discretized time series. Various techniques can be employed to categorize time series data into bins.
A recurrence plot is an image that is generated from a time series and illustrates the pairwise Euclidean distances for each value (and, more broadly, for each trajectory) in the time series. A threshold can be implemented to binarize the image.

TS to Graphorm representation

Graphing the time series or displaying data is crucial and typically serves as the initial stage in any investigation. We have various graphing formats, including:

Singular Spectrum Analysis

Time series are a combination of trends and noise. Decomposing time series into numerous time series can help preserve key information. One decomposition algorithm is Singular Spectrum Analysis. Temporal subseries include trend, seasonal, and noise. Decomposing time series into these components can help characterize the signal.

Complex Networks

With the rise of "big data," huge amounts of time series data are being created very quickly in many different areas. The data is complicated because it is not linear and has a lot of different distribution trends. Complex networks are a new way to look at nonlinear time series analysis, and they have been used a lot. On the basis of the dimensionality of time series, the resulting network structure, the mapping concept, and the primary mapping methods, Figure 4 shows an overview of the survey proposed in [1]. It is a taxonomy of algorithms for mapping time series into complex networks.

The Graphormer model

It was proposed in [14]. The Graph Transformer model has been changed so that it can work with graphs instead of text strings. To do this, relevant embedding's and features are created during pre-processing and collation, and then better attention methods are used.

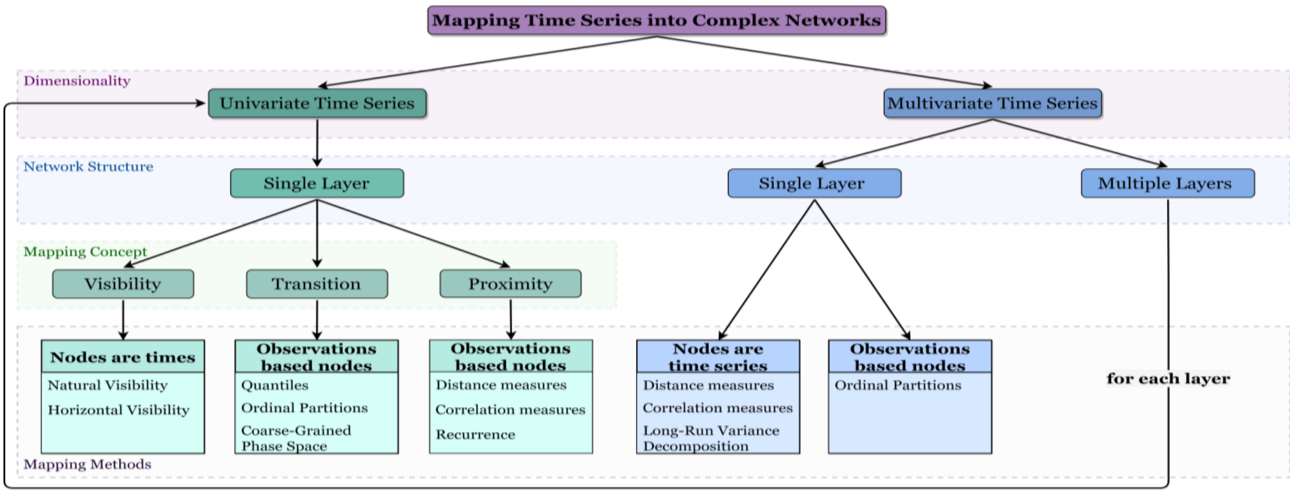


Figure 4. Overview of the survey proposed in [1].

3.1 TS Transformation Application Algorithms

TS to TS representation applications

Several algorithms employ these representations for making predictions and classifications. Figure 5 shows many classification methods utilized by these representation schemes. Bagnall et al. [15] conducted a review and experimental evaluation of recent advancements in classification algorithms. It was indicated that there remain several fundamental issues with the published time series classification (TSC) research that they aim to address. Time series forecasting algorithms can be categorized into traditional statistics models, machine learning models, and hybrid models. The authors Shah and Thaker [16] carried out a comparative analysis of a number of different time series forecasting algorithms that are now available. They investigated the problems associated with time series forecasting as well as the solutions that are currently available. The subsequent examples demonstrate various algorithms that utilize Time Series Transformations.

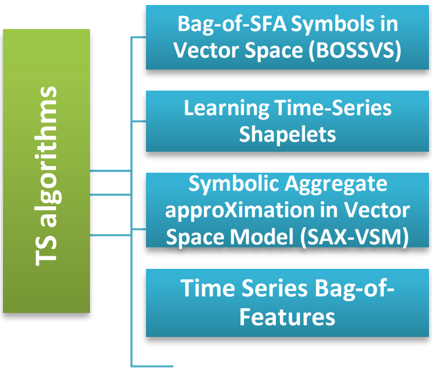


Figure 5. Various algorithms utilize time series transformations.

Symbolic Aggregate approXimation in Vector Space Model (SAX-VSM):

A collection of time series and associated labels is converted into a document-term matrix using tf-idf statistics via the SAX-VSM algorithm. Every class is represented as a tfidf vector. For an unlabelled time series, the label of the tfidf vector that has the maximum cosine similarity to the tf vector of the unlabelled time series is the predicted label.

Bag-of-words methods are frequently used in the classification of time series data. The Bag-of-patterns approach employs a sliding window technique to extract subsequences from the time series. It then converts each subsequence into a word using the Piecewise Aggregate Approximation and Symbolic Aggregate approXimation algorithms. Consequently, it converts each time series into a collection of words. Next, it calculates the frequencies of each word for each time series.

Dictionary-based classifiers exhibit identical overarching structures. A series is traversed via a sliding window of a specified length. Each window undergoes approximation and discretization techniques to turn the real-valued series of a certain length into a symbolic string of a different length. This symbolic string is composed of possible letters.

Bag-of-SFA Symbols (BOSS) algorithm: Each time series undergoes transformation into a histogram through the application of the Bag-of-SFA Symbols (BOSS) algorithm. Subsequently, for each class, the histograms are aggregated, and a tf-idf vector is calculated. The class assigned to a new sample is determined by identifying the class that exhibits the highest cosine similarity with its tf vector in relation to the tf-idf vectors of all classes.

The LearningShapelets algorithm learns in the training phase. A shapelet is defined as a contiguous subsequence of a time series. The distance between a shapelet and a time series is defined as the minimum of the distances between this shapelet and all the shapelets of identical length extracted from this time series. This estimator consists of two steps: computing the distances between the shapelets and the time series, then computing a logistic regression using these distances as features. This algorithm learns the shapelets as well as the coefficients of the logistic regression.

In the time series bag-of-features (TSBF) approach, the feature significance scores of the final random forest classifier are the metrics that are considered. The following steps are involved in fitting this algorithm:

Subsequences are systematically extracted from each input time series.
Each subsequence is divided into multiple intervals.
From each interval, three features are extracted: the mean, the standard deviation, and the slope.
Four features are extracted from the entire subsequence: the mean, the standard deviation, and the start and end indices.
A random forest classifier is initially fitted on this dataset of subsequences, with the label of each subsequence determined by the label of the corresponding time series from which it was extracted.
The out-of-bag probabilities for each class are aggregated across all subsequences derived from a specific time series, and the mean probability for each class is calculated as well. The features have been extracted from the original data set.
A second random forest classifier has been successfully fitted utilizing the extracted features.
TS to TS Representation Computations
In the area of time series classification (TSC), SAX-based classifiers suffer from high running times and are negatively affected by noisy data [17]. The Symbolic Fourier Approximation (SFA), and its classification frameworks (BOSS,

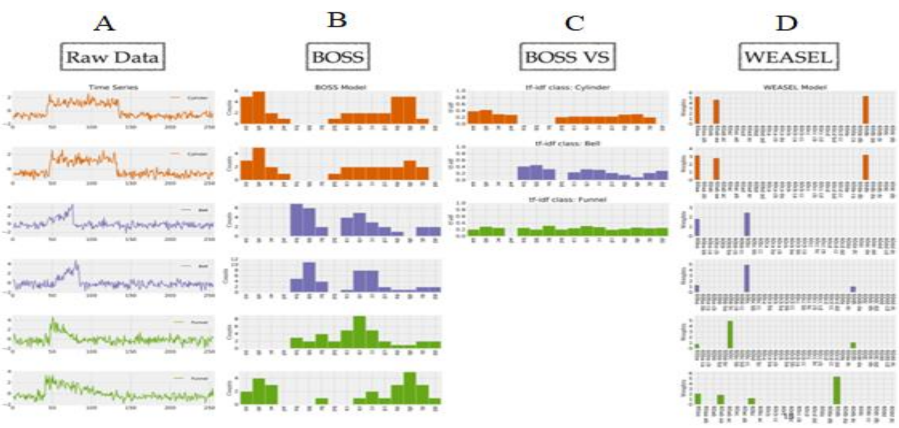


Figure 6. (A) Raw data, (B) The BOSS model as a histogram over SFA words. It first extracts subsequences (patterns) from a time series. Next, it applies low-pass filtering and quantization to the subsequences using SFA which reduces noise and allows for string matching algorithms to be applied. Two time series are then compared based on the differences in the histogram of SFA words. (C) The BOSS VS model. The BOSS VS model extends the BOSS model by a compact representation of classes instead of time series by using the term frequency - inverse document frequency (tf-idf) for each class. It significantly reduces the computational complexity and highlights characteristic SFA words by the use of the tf-idf weight matrix which provides an additional noise reducing effect. (D) The WEASEL model. WEASEL conceptually builds on the bag-of-patterns model. It derives discriminative features based on dataset labels. WEASEL extracts windows at multiple lengths and also considers the order of windows (using word co-occurrences as features) instead of considering each fixed-length window as independent feature (as in BOSS or BOSS VS). It then builds a single model from the concatenation of feature vectors. It finally applies an aggressive statistical feature selection to remove irrelevant features from each class. This resulting feature set is highly discriminative, which allows us to use fast logistic regression.

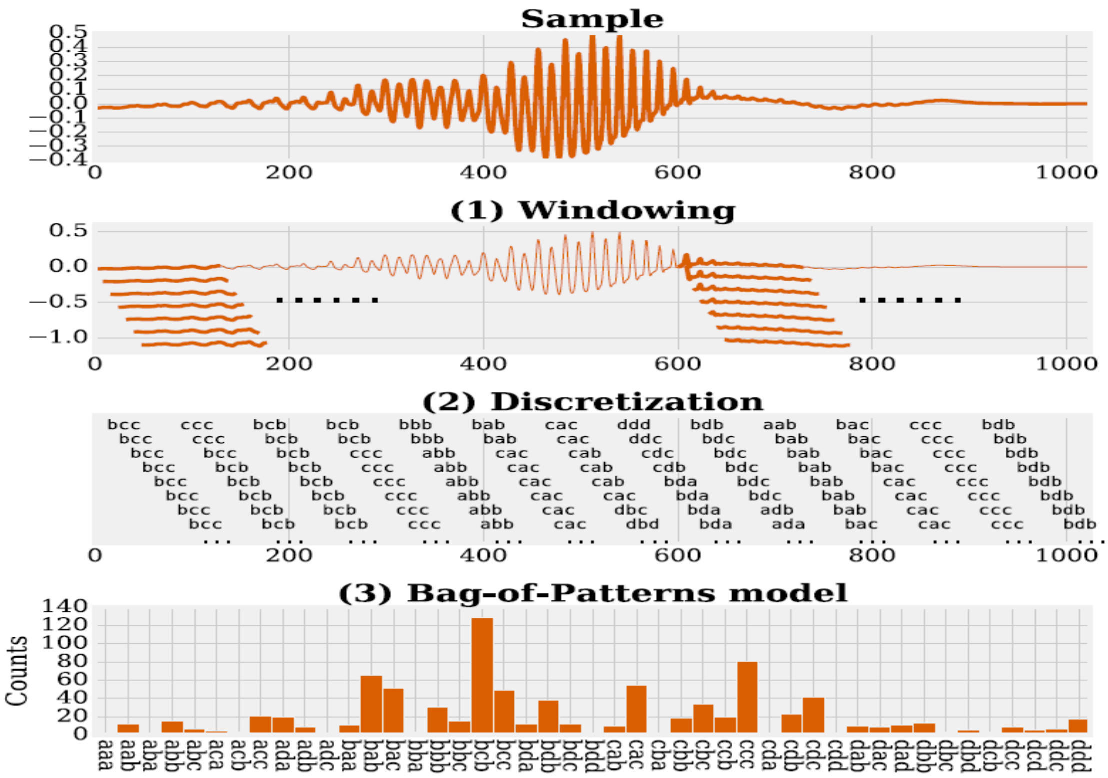
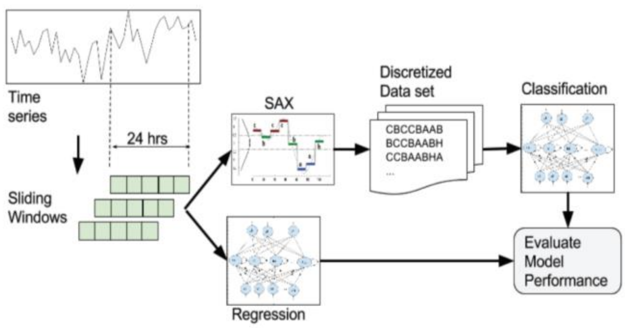


Figure 7. TS is changed into a dictionary-based model [1].

(a)



(b)

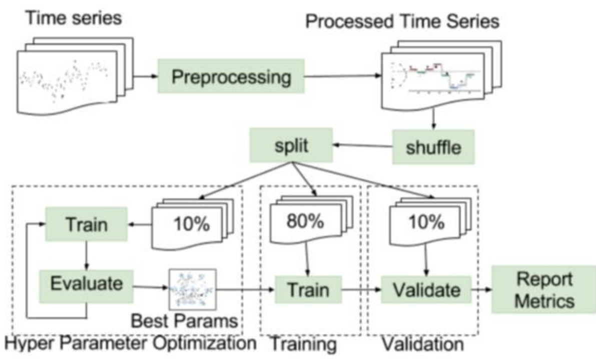


Figure 8. (a) Overview of the components and processes. (b) Artecher that make up the proposed system in [22].

WEASEL and MUSE) [18, 19, 20], have further advanced both accuracy and efficiency. Figure 6 shows SFA classification frameworks. Figure 7 shows how a TS is changed into a dictionary-based model. Schäfer, Patrick & Leser, Ulf [21] introduced WEASEL 2.0, a dictionary-based TSC method with competitive classification accuracy. Unlike its predecessors (BOSS, WEASEL, TDE), it is quick and maintains a consistent memory footprint. This makes it suitable for high-runtime and precision domains. Naduvil-Vadukootu et al. [22] provided the preprocessing pipeline that is comprised of a number of steps that are designed to compress the input time series and transform it into a representation that is acceptable for the application of deep learning models. To investigate whether or not deep learning algorithms are suitable for predicting time series data, they extended the sequence prediction approach. Figure 8 shows detailed information regarding the components and procedures that make up their system.

TS to network Representation Applications

One more interesting method is a fuzzy interval time-series forecasting model that uses network-based multiple time frequency-spaces and the induced-ordered weighted averaging aggregation (IOWA) operation. Liu et al. [23] suggested the model for energy and finance forecasts. Currently, the time series network approach is a popular area of research. Furthermore, there is considerable potential for further growth, particularly in the comparative analysis of network methodologies and conventional approaches.

The real systems factors are very complicated in interacting with each other [24, 25]. A complex network has a close relationship with the time series [26, 27], and it can be used to identify time series information [28, 29]. Jonathan F. Jonathan Donges, et al. [30] provide powerful tools for the study of complex systems in various disciplines for network theory and nonlinear time series analysis such as climatology, neuroscience, social science, infrastructure, or economics. F. Strozzi, et al. [31] presented the idea is to build up a bridge between complex networks and time series. Andriana Campanharo, et al. [32] proposed a map from a time series to a network with an approximate inverse operation, making it possible to use network statistics to characterize time series and time series statistics to characterize networks. A Complex network can also make predictions through reasonable analysis [33].

Recently, combining both network theory and nonlinear time series analysis has yielded a wealth of new approaches for understanding and modeling the structure and dynamics of such systems based on the statistical analysis of networks or uni- and multivariate time series. Guangyu Yang, Daolin Xu, et al. [34] proposed a novel method based on epsilon-recurrence networks for the study of the evolution properties of dynamical systems.

TS to network Representation Computations

S. Mao and F. Xiao [35] proposed a novel method for more accurate time series predictions. First, time series data are mapped into a network by visibility graph. Then, the link prediction method is adopted to calculate the similarity index. Considering that node distance is an important factor in the network, we take that into account to determine the weight coefficients and improve the predictive results. Figure 9 shows the proposed method that is encapsulated in Algorithm 1.

Song and Fuyuan [36] proposed an effective and accurate method in conducting EEG signal fusion. The authors converted a time-series Combining basic probability assignments (BPAs) into a weighted visibility graph (WVG) so a new evidence fusion approach based on belief entropy and a visibility graph (BE-VG) is applied to Electroencephalogram (EEG) dynamic fusion. Hu Y and Xiao F. [37] proposed a novel forecasting method for time series, that can efficiently capture the spatio-temporal dependency. The authors presented a novel network constructing model called fuzzy cognitive visibility graph (FCVG) for time series to convert the time series into a pair of directed weighted graphs. They developed the weighted multi-subgraph similarity (WMSS) to calculate the similarity between nodes in FCVG.

Dimitrios and Lykourgos [38] proposed a novel method for studying the evolution of the Greek COVID-19 infection curve in relation to the anti-COVID-19 policies applied to control the pandemic. Based on the ongoing spread of COVID-19 and the insufficient data for applying classic time-series approaches, the analysis builds on the visibility graph algorithm to study the Greek COVID-19 infection curve as a complex network. Figure 10 shows shows the visibility graph generated from the time-series. A multi-modal fuzzy cognitive map (FCMs) was suggested by Feng Guoliang et al. [39] as a tool for time series modeling. Figure 11shows an example of Fuzzy cognitive graph (FCMs)

(a)

Algorithm 1 The process of the proposed method

Input: Time series dataset T: N data values
Output: The prediction value of $\hat{y}_{N+1}$
function TIME SERIES PREDICTION
  Transform time series T into a graph
  Calculate node similarity S_{xy}^{SRW}
  Find two most similar points (t_M, y_M) and (t_N, y_N)
  Determine node distance $d_{M \to N}$
  $y_{N+1} \leftarrow y_N + \frac{y_N - y_M}{t_N - t_M}(t_{N+1} - t_N)$
  $\hat{y}_{N+1} \leftarrow w_{N+1} \times y_{N+1} + w_N \times y_N$
  return $(t_{N+1}, \hat{y}_{N+1})$
end function

(b)

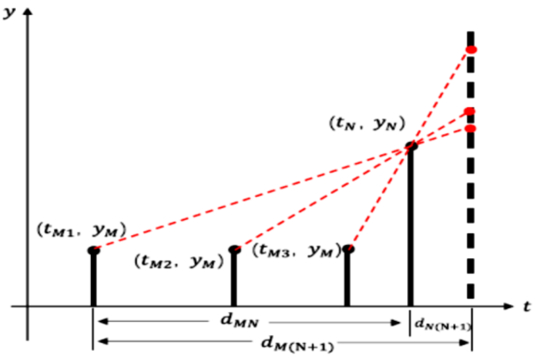


Figure 9. (a) Algorithm 1 of the proposed method. (b)The description of visibility graph: When the node (tM, yM) goes from tM1 to tM3, the distance dM→N decreases, indicating that the distance decreased. The information that node (tM, yM) holds about the past is not as important and is weaker. Copied from [35].

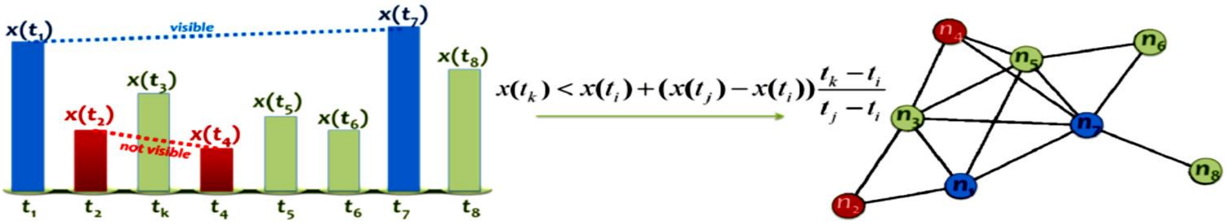


Figure 10. An example of visible and non-visible nodes using the NVG algorithm is displayed on the left, and the graph formed from the time series is presented on the right [38].

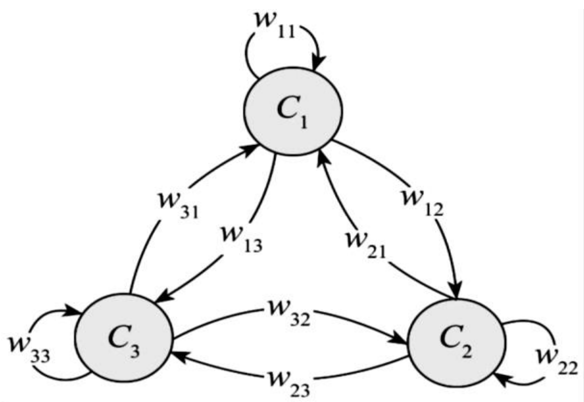


Figure 11. Fuzzy cognitive graph (FCMs) with three nodes. Copied from [39].

TS to image representation applications

According to Sharma, Alok, et al. [40], the DeepInsight technique integrates elements arrangement, feature extraction, and classification to enhance classification performance in non-image data. This collaborative method uncovers underlying mechanisms and connections between properties. The technique enhances relevance and resilience by integrating similar characteristics as clusters, facilitating the incorporation of essential information from weaker elements rather than addressing individual features. The arrangement of elements is essential for accessing vital information and accomplishing objectives. Table 1 sumurise some results and advantages of many applied techniques.

Table 1. Comparison of TS to image representation applications methods.

S/N	Method	Description	Advantages and results
1	Zhen Zeng et al. [41] suggest employing video prediction to forecast economic time series for various financial assets.	Their goal is to predict financial asset prices using past data. They use CNNs to get a hidden picture of financial assets by putting prices at different times into a 2D picture, which is similar to showing how markets change. This represents the price history as a sequence of photos, and the purpose is to anticipate future images.	They improve computer vision for video prediction.
2	Sood, Srijan , et al, [42] tackle the challenge of time-series forecasting inside computer vision	They take input data like an image and train a model to produce output. This technique forecasts distributions, not points. To assess the method's strength and quality, they use a variety of evaluation indicators and study a variety of datasets.	It was found that the forecasting method works well for cyclic data but less well for irregular data like stock prices. When using image-based assessment metrics, their system outperforms ARIMA and a numerical counterpart of our deep learning technology.
3	Chao-Lung et al [43] looked at how using different transformation methods affected the accuracy of classification.	They converted time series data into three two-dimensional colored images: the Gramian Angular Summation Field (GASF), the GADF, and the MTF. They combined the images into one and sent it to a Convolutional Neural Network (CNN) for classification.	In their study, transformation methods and concatenation order had no impact on prediction.
4	Nima et al. [44] employed Recurrence Plots (RP) to convert time series into 2D texture images before applying the deep CNN classifier.	Since time-series visual representation has various feature types than 1D signals, Time-Series Classification (TSC) can be considered a texture image identification work. CNN models can also automatically learn many representation levels with classifiers.	As a result, the combination of RP and CNN ought to result in an increase in the recognition rate of TSC.
5	Morid et al. [45] analyzed three years of medical and pharmaceutical claim data.	The multivariate time series of cost, visit, and medical variables were modeled as patient health images. Patients' multivariate time series data should be converted	This approach holds promise for implementation in various other healthcare contexts that utilize multivariate time series data.

S/N	Method	Description	Advantages and results
		into images and refined for convolutional learning.	
6	Li, Xixi et al [46] Forecasting with time series imaging	Extract time series features from time series imaging in two phases. First, we encode time series into visuals using recurrence plots. The second phase extracts time series features from photos using image processing. We compare the spatial bag-of-features (SBoF) model and convolutional neural networks for visual feature extraction.	Forecasting using time series imaging gives us an automatic way to pull features from time series. This means that we don't have to do a lot of work to choose which features to use, which is very important for people who make forecasts.
7	Yang Chen, et al. [47] converted the multivariate time series of SWAN-SF dataset into multi-channel images	Using many image methods to rethink flare forecasting. They said the image classifier was purposely simplistic to match the SVM-based classifier they used.	The analysis of the results indicated no enhancements in the classification of flaring and non-flaring instances when utilizing derived images.

TS to image representation Computations

In time series forecasting research, data augmentation is commonly employed, serving as an injection of prior knowledge regarding data invariance for specific transformations.

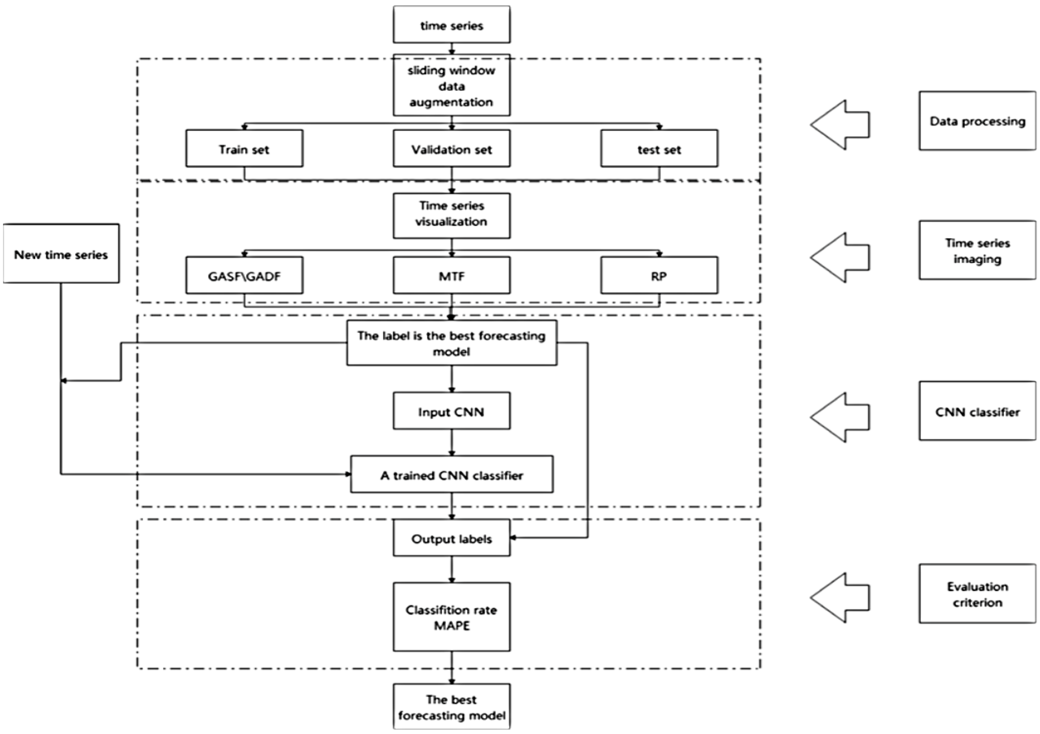
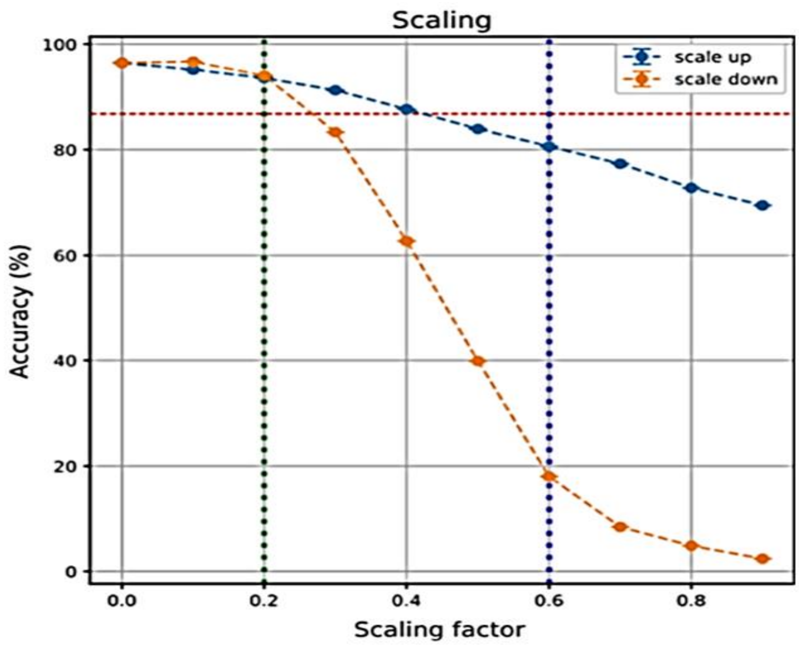


Figure 12. CNN-based Forecast-model Selection framework [48].

The augmentation method is considered for extending the datasets. Jiang, Wentao et al [48] proposed the CNN-based Forecast-model Selection (CFMS). They utilized several time series populations as samples to train the classification algorithm. Consequently, the recently added time series in this framework is viewed as extra data that is comparable to the training set's data type, or what is known as the "target type" of time series. Through the process of simulating and expanding the data that is comparable to the time series of the training set, it is possible to enhance the accuracy of the classification. Figure 12 shows their proposal frame. Additionally, they add that cropping, which is similar to image clipping, lessens the dependency on the location of the event to yield the best sliding window step. It's important to remember that clips may keep parts that aren't informational, which could lead to label changes. Small changes like dithering, zooming, clipping, twisting, and spinning may not change the data label as much as they do with image recognition. Mooseop Kim et al.[49] conducted a comparison of the impact of data augmentation methodologies with varying window slicing ratios on sensor data. Figure 13 shows the results. They demonstrate that when the scaling factor is 0.1, or the length of the time series slice window is 90% of the original length, the classification accuracy is greatest.



$$y = a \cdot e^{\frac{-(x-0.1)^2}{b}} \qquad 0 \ll x \ll 1$$

Figure 13. Comparison of classification accuracy and scaling factor. Based on [49], a mathematical formula is fitted using the known data and the orange line. In this equation, y represents the classification rate, x represents the scaling factor, and a & b can be thought of as constants. One can infer that the local Gaussian function reaches its maximum when the scaling factor x is equal to 0.1.

The Gramian Angle Summation Field (GASF), the Gramian Angle Difference Field (GADF), and the Markov Transition Field (MTF) are the four algorithms that are employed to convert time series into images. [48] Provided a concise summary of the mathematical computations that are utilized in the process of carrying out these algorithms.

4. Image Representations

After getting an image, it is important to devise ways to represent the image. The simplest way to represent the image is in the form of a matrix. Image representation plays an important role in the optimization of different image processing operations. Each of the image representation method achieve some better results in some particular image processing application [50].

Image to Graph representation or TS

Image processing is a multidimensional signal processing that is used to enhance, modify, extract information, compress, and transform images which are nothing but multivariate signals. An image histogram is a type of histogram that acts as a graphical representation of the tonal distribution in a digital image. It plots the number of pixels for each tonal value. Histogram of oriented gradients (HOG) is a feature descriptor used in computer vision and image processing for the purpose of object detection. The technique counts occurrences of gradient orientation in localized portions of an image. Figure 14 shows HOG feature for an image.

(a) (b)

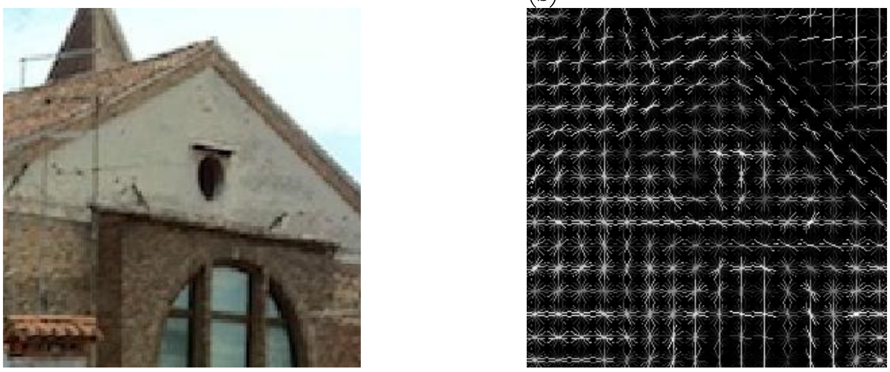


Figure 14. (a) An image, (b) Histogram of oriented gradients (HOG) of the image in (a).

Image to Complex network representation

In the graph-based approach, a segmentation S is a partition of V into components such that each component (or region) C ∈ S corresponds to a connected component in a graph G = (V, E), where E ⊆ E. A. Sanfeliu, et al.[51] described several applications of graph-based representation and techniques for image modelling, processing.
Andrey Trufanov, et al [52] proposed an approach to convert image data into genuine complex networks and further to assess topological properties of synthetic and real digital pictures has been proposed. This implies partition a multipixel image into 3 category levels which correspond to local, proximal, and global regions (superpixels) and specific links among the pixels respectively to the connected regions.

4.1 Image Transformations and Applications

Figure 15 shows the three different applications for image representation schemes.

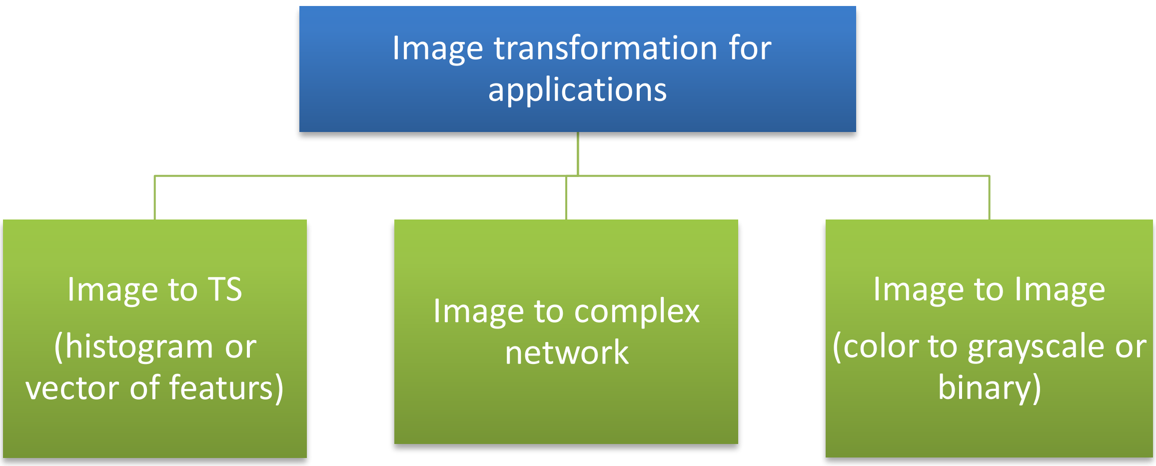


Figure 15. Various image representation schemes.

Image to TS representation Aplications

The Local Binary Pattern (or LBP for short) texturing operator is simple yet quite powerful. To do this, it thresholds the region around each pixel and then treats the result as a binary integer; this is how it labels the image's pixels [53].

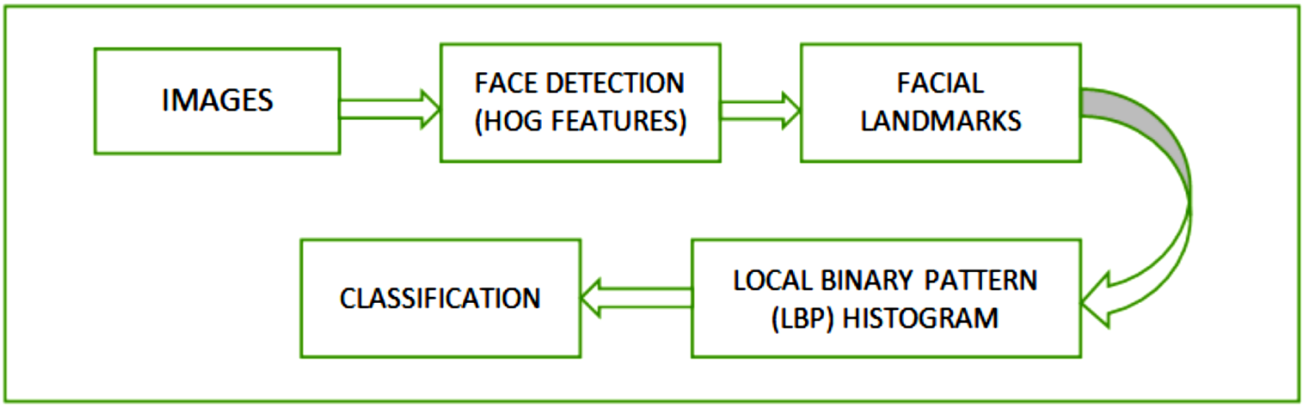


Figure 16. Practical Procedures for image classification.

Figure 16 shows practical procedures of face expression classification. Using a number of python libraries some of which include:

OpenCV Library — for importing photos into channels.
Scikit-Image Library – for the purpose of denoising photos with a wavelet denoiser.
Pandas Library – the correlation between the images in our collection was computed and made visible with the help of this tool. It was also used to store flattened versions of our images in a structure that reminded us of a table and was called a Data frame. This structure was used to store the imags.
Scikit-Learn Library – for using Hierarchical clustering on the pictures that have been flattened.
Matplot Library – which is a component of the Anaconda distribution, was also utilized to execute scripts in this study, enabling the Python scripts to be run piece by piece, and for visualizing our clustering techniques. This makes debugging and incremental development easy. Figure 17 shows extracting local binary pattern for an input image.

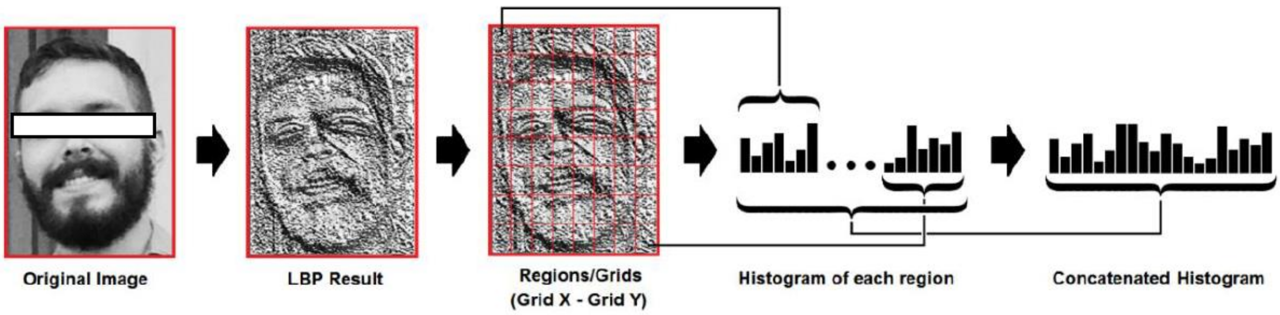


Figure 17. Extracting local binary pattern.

In the field of Choosing Time-Series Thermography as the Feature Representation. Time-series methods have been widely employed in infrared physics to increase detection performance by describing thermal properties spatially across time. Banerjee, Soumya, et al. [54] demonstrated a successful use the time series generated from high content thermal imaging videos of patients suffering from the aqueous deficient dry eye (ADDE) disease.

Image to Complex Network representation Applications

There have been very few works that have been done up until this point that handle images as complex networks in the context of image analysis and recognition challenges [55, 56].

In medical diagnostic imaging, T2-weighted brain image series to facilitate a better understanding of how and why a specific judgment was made; Tachibana et al [57] proposed an approach involving applying various preprocessing steps to the input image data to isolate the most crucial features that will be used to make the final decision.

Josimar E. Ch. S. and Esteban W. V. Z. [58] explored the structure of pattern behind covid-19 dataset of medical images with positive and negative cases. They took a sample of 100 images, 50 per each class. Calculating the histogram frequency to get features by statistical measurements, besides a feature extraction using Grey Level Co-Occurrence Matrix (GLCM). Using both features are build Complex Networks respectively to analyze the adjacency matrices and check the presence of patterns.

Aksac et al. [59] converted an image into superpixel segments that encompassed similar pixels, thereby creating compact regions.

Trufanov et al. [60] proposed a method to transform image data into authentic complex networks and subsequently evaluate the topological properties of both synthetic and real digital images. This means that a multipixel image should be divided into three category levels, each of which represents a local, proximal, and global region (superpixel), as well as a particular link between the pixels and the related regions.

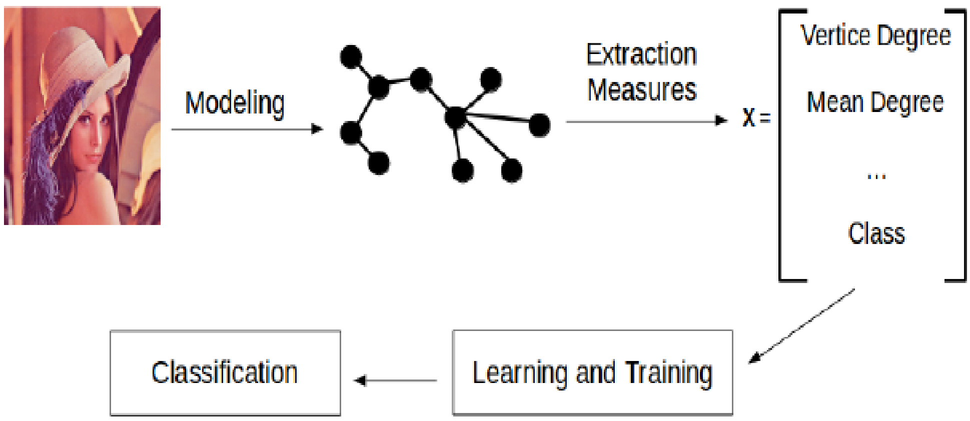


Figure 18. Pipeline of the proposed methodology in [61].

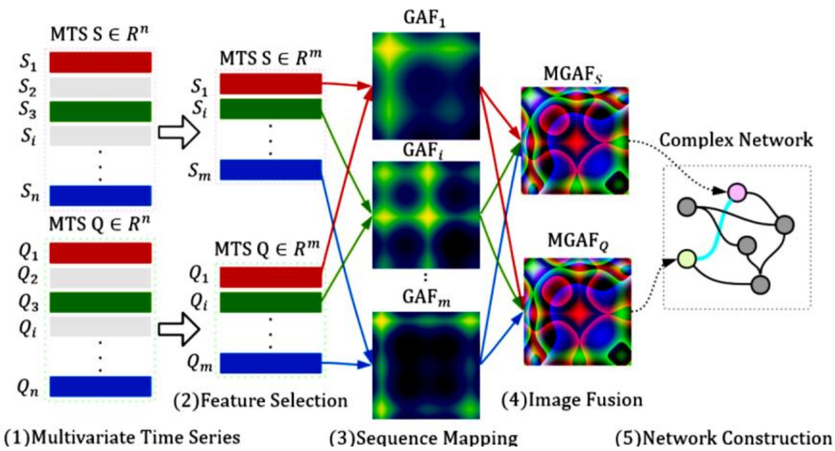


Figure 19. Architecture of the proposed method. The whole process of the proposed method contains five steps. (1) Selected representative sub-time series to form a new multivariate time series (MTS). (2) Converted sub-time series to a Gramian angular field (GAF) grayscale image. (3) Fused multiple grayscale images into a color image. (4) Added nodes to the complex network. (5) Determined edges between nodes by the similarity between fused images [62].

Geovana V.L. de Lima, et al. [61] proposed a complex network-based approach to the Analysis and Classification of Images. Zongwen Huang et al. [62] stated that standard commercial complex networks fail to properly use the many features of stocks and redundant filtering relationships, hence not accurately representing the financial stock market; consequently, they offered a novel way to address this issue. Figure 19 shows their proposed methodology.

Recent Advances

Recently; Imene Mitiche et al. [63] suggested a new algorithm for Electromagnetic Interference (EMI) discharge source characterization. Images were used to build new and improved feature extraction and data dimension reduction algorithms. They employed Gramian Angular Field to map measured Electromagnetic Interference (EMI) temporal signals into image and remove redundancy to recover key information. They said each discharge type's image has a fingerprint, and the classification results improved over previous work. The research states that noise and artefact structures in many CXR images can obscure diagnostic findings [64]. Such changes allow us to produce distance maps that show edges and the general architecture of organs like the lungs for reliable pneumonia detection. The various distance maps generated by the Euclidean distance transformation (EDT) can serve as an additional source of information for deep learning models, complementing the input intensity-based [65, 66]. This would also improve the model's ability to detect features, especially regarding the presence of infiltrates or consolidations in the lungs. Furthermore, the EDT has the potential to standardize the distribution of different shapes in space, thereby enhancing the stability of the models and reducing their sensitivity to variations in patients and imaging [67].

Yeasmin [68] explains and compares some contemporary methodologies utilized in medical imaging Computer-Aided Diagnosis (CAD) systems. The paper provides a thorough and well-structured assessment of CAD in medicine, using well selected publications. It also explains medical image management and introduces cutting-edge AI-based CAD technologies and CAD's future. This study shows that deep learning algorithms are best for disease diagnosis.

5. Evaluation

In addition to the type of data, Sarker et al. [69] came to the conclusion that the efficiency and efficacy of a machine learning-based solution will be determined by the performance and features of machine learning algorithms.
Utilizing a variety of machine learning domains, such as reinforcement learning, association rule learning, dimensionality reduction and feature selection, data clustering, regression, and classification analysis, in order to design data-driven systems in an efficient manner is possible.

Jhaveri et al [70] introduced a comprehensive Review on Machine Learning Strategies for Real-World Engineering Applications that enhances the comprehension of the relevance of diverse machine learning methodologies in practical scenarios, including cyber security, healthcare, and intelligent transportation systems. Also; recent findings indicate that deep neural networks necessitate a significant volume of training data; otherwise, their ability to generalize may be compromised. Data augmentation strategies are employed to improve the generalization capabilities of the network by leveraging a broader spectrum of training data. It is feasible to generate new data that is a modified version of the original data by utilizing common data augmentation techniques such as flipping and scaling. This is a possibility. Generative Adversarial Networks, commonly referred to as GANs, are designed to generate new data that can serve a beneficial purpose.

Wali et al. [71] presented a new GAN model, StynMedGAN, aimed at the synthetic production of medical images to improve the effectiveness of classification models. StynMedGAN is an enhancement of the advanced styleGANv2, which has produced remarkable results in generating diverse natural images. A regularization term was incorporated as a normalized loss component within the current discriminator loss of styleGANv2. Radiology X-rays, computed tomography scans, and magnetic resonance imaging (MRI) all have their own unique properties. They showed that styleGANv2's capabilities are improved by the suggested GAN, making medical imagine management easier. The recently created GAN model, StynMedGAN, is used to generate extra data for classification tasks across three types of medical imaging: X-rays, CT scans, and MRI. The proposed model for classification is evaluated using three different classifiers: CNN, DenseNet121, and VGG-16. This is done in order to determine how effective the methodology is. Classifiers learned using data enhanced by StynMedGAN outperform those trained using just the original dataset, according to the results. The findings point to a promising resource that practitioners and radiologists may use to diagnose a variety of disorders. A comprehensive introduction to image data augmentation techniques that directly improve already existing samples as well as techniques that generate new samples by utilizing GAN models is included in Zeng and Wu's [72] contribution.

Ramadan et al. [73] conducted a recent review of a particular category of deep learning-based medical image registration techniques, with a specific emphasis on Transformer-based methods. The development of Transformers in Natural Language Processing has seen significant examination of Vision Transformers (ViTs) across multiple applications in medical imaging, particularly in the area of image registration. The main aim of the study is to analyze the diverse models found in the literature for medical image registration using Vision Transformers (ViTs) and to classify them from various viewpoints, highlighting the methodology employed in the application of Transformers in each approach. The study presents and analyzes twenty-nine publications published from 2021 to 2024 toward this objective. Furthermore, they provide a comprehensive examination of the diverse attention processes and Transformer versions employed in registration structures to furnish researchers with extensive information.

6. Conclusion

In this paper we introduced an approach to recognize the transformations of two types of data forms the time series data form and the image data form. We have presented a small review on the findings brought to light the reciprocal benefit that exists between different representation strategies and the influence that these strategies have on prediction and classification tasks for time series and images. This demonstrates that there is a relationship between the two that is constructive for both parties involved. All the studies we presented had the main goal to improve the models' accuracy, and make the models simpler to understand. Within the framework of this presentation, we discussed the benefits that come with making improvements to previous models. Upon further investigation, it was found that there were a few applications. Every machine learning algorithm has a particular goal, and even those in the same category will produce different results depending on the data. The selection of a learning algorithm to solve a target domain is difficult. Thus, understanding the applicability and underlying principle of ML algorithms in real applications is necessary.

In recent times, the field of medical imaging has witnessed a significant amount of success in the use of artificial intelligence (AI) that is founded on the concept of deep learning. Additionally, we took note of the prospective future direction that would be worth considering increasing the work on because of its potential. This is because it is superior in terms of extracting features, which is the reason for this statement. Over the past few days, we have made reference to a review that was carried out on a specific family of deep learning-based medical image registration algorithms, with a specific emphasis on Transformer-based techniques.

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The author has declared that no competing interests exist.
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Use of AI tools declaration
The author declares that she has not employed artificial intelligence (AI) instruments in the development of this article.

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