REVİEW ARTICLE

Encoding IoT Data: A Comprehensive Review of Image Transformation Techniques

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ABSTRACT

In the era of the Internet of Things (IoT), where smartphones, built-in systems, wireless sensors, and nearly every smart device connect through local networks or the internet, billions of smart things communicate with each other and generate vast amounts of time-series data. As IoT time-series data is high-dimensional and high-frequency, time-series classification or regression has been a challenging issue in IoT. Recently, deep learning algorithms have demonstrated superior performance results in time-series data classification in many smart and intelligent IoT applications. However, it is hard to explore the hidden dynamic patterns and trends in time series. Recent studies show that transforming IoT data into images improves the performance of the learning model. In this paper, we present a review of these studies that use image transformation/encoding techniques in the IoT domain. We examine the studies according to their encoding techniques, data types, and application areas. Lastly, we emphasize the challenges and future dimensions of image transformation.

Keywords: Internet of Things, Time-series, Image transformation, Image encoding

1. Introduction

The Internet of Things (IoT) refers to a network of intelligent physical devices embedded with sensors, software, and cutting-edge technologies that empower them to establish connections and share data with other devices and systems via the Internet [1]. In other words, smartphones, wireless sensors, built-in systems, and nearly every device are connected and communicate via a local network or the internet. Some of the IoT applications include smart homes [2], smart cities [3], smart agriculture [4], smart health [5], smart retail [6], etc.

The proliferation of IoT and the growing number of IoT devices have led to the generation of immense volumes of time-series data. Consequently, time-series analysis has been performed extensively across a diverse spectrum of IoT domains [7, 8]. Traditional time-series analysis methods have accomplished convenient performance with hand-crafted characteristics and satisfactory expert knowledge. On the other hand, these methods may not always be suitable for examining IoT time-series data due to unique features that distinguish it from non-IoT time-series data [9]. Analyzing time-series data for IoT devices presents challenges due to its complex nature, unlike non-IoT time-series data analysis. IoT time-series data can be quite complex, with spatial and temporal correlations that are often difficult to manage. In addition, many IoT applications require real-time or near-real-time data processing in order to make timely decisions, which can be technically challenging and require specialized infrastructure. Encoding methods offer significant advancements in feature extraction, pattern recognition, and the performance of machine learning and deep learning compared to traditional time-series analysis methods, such as statistical approaches and classic machine learning techniques. Traditional time-series analysis often struggles to effectively capture the complex and non-linear patterns inherent in IoT data and is not particularly strong in preserving temporal dependencies. In contrast, image transformation techniques uncover hidden spatial patterns while maintaining temporal dependencies. Moreover, traditional methods require manual feature engineering, whereas image encoding techniques facilitate automatic and comprehensive feature extraction. Additionally, image transformation techniques leverage powerful deep learning architectures originally designed for image processing.

To address these challenges, image transformation/encoding techniques have been proposed as promising technologies that transform time-series data into visual representations, enabling easier analysis and interpretation. In addition, transforming the data into an image and applying image compression techniques like JPEG or PNG can reduce the data size while preserving essential information. Compressed image representations of time-series data can be stored or transmitted more efficiently. In recent years, researchers have focused on time-series data transformation into an image format because of the

great success achieved in the IoT domain, particularly in applications such as anomaly detection, fault diagnosis, and activity recognition.

In this study, we conduct a comprehensive survey of image transformation techniques from several perspectives. Initially, we scrutinize existing studies based on their transformation techniques and subsequently categorize them according to data types (univariate or multivariate) and application domains. To the best of our knowledge, no prior survey paper has investigated the utilization of image transformation techniques in the realm of IoT. To bridge this gap, our paper presents an in-depth analysis of the current research landscape within the IoT domain.

1.1. Motivation

The fundamental idea of improving a model is to change it to another model that has higher accuracy. Many researchers apply combining models such as hybrid models or pre-trained models [10-13]. However, it is worth considering whether model accuracy can be improved without altering the model itself. Some studies suggest that the transformation of time-series data may be a more effective approach for improving model accuracy than changing the model itself [14-16].

There are several advantages of representing IoT data as images: i) It becomes easier to visualize and analyze complex patterns or trends. ii) It provides visual representations of temporal data, allowing for intuitive interpretation and pattern recognition. iii) It is an effective way to reduce dimensionality while maintaining temporal dependencies, leading to more efficient analysis and better insights. iv) Deep learning techniques can be effectively employed to analyze IoT time-series data in image-based analysis for IoT applications such as pattern classification or healthcare monitoring.

By highlighting the aforementioned advantages, this review paper enables researchers to make informed decisions about the techniques that are most suitable for achieving their objectives. Therefore, it can act as a valuable guide on effectively using advanced image transformation methods in real-world scenarios by providing a comprehensive summary of the current state-of-the-art. Moreover, this paper answers questions such as which techniques were employed in specific IoT applications and which yielded more successful results.

1.2. Research Methodology

Once the motivation for the study is identified, a research methodology is determined. This methodology provides an overview of the approach and details the systematic procedures used in the paper selection process:

• Literature Search Phase: The first step involves the selection of specific search phrases relevant to the topic. These search phrases include "Image Transformation", "Image Encoding", "Time-Series Data in IoT", and "Time-Series Imaging in IoT". Related papers have been retrieved from various digital libraries such as ScienceDirect[1], IEEE Xplore[2], and Springer[3].

• Paper Selection Phase: We applied the following criteria to identify which papers should be excluded from this study: (i) Papers without peer review; (ii) White papers; and (iii) Papers not directly related to IoT.

• Paper Classification Phase: We selected 39 papers that focus on Time-Series to Image Transformation in IoT and satisfy our selection criteria. These papers were divided into categories according to the type of time-series data and IoT domain as follows: 5 in Security, 6 in Energy Management, 12 in Healthcare, 8 in Industrial, 1 in Environmental Monitoring, 1 in Smart Building, 1 in Transportation and Logistics, and 1 in Wearable Devices, and 4 in other domains which not contain any specific domain. Table 3 presents an overview of these 39 articles by categorizing them according to nine IoT domains. In Addition, Table 2 summarizes 24 univariate papers, 12 multivariate papers, and 3 papers covering both types.

1.3. Contribution

Image transformation stands as a significant innovation with the potential to enhance outcomes not only in the realm of IoT but also across various other domains. To the best of our knowledge, no existing study reviews image transformation techniques in the realm of IoT. The contributions of this paper are summarized as follows:

• This study introduces the first survey paper that summarizes time-series transformation techniques in IoT.

• We provide a comprehensive comparison of recent studies according to their encoding techniques, data types, and application areas in the IoT domain.

• We present challenges and future directions of transforming time-series into images in the context of IoT.

1.4. Organization

The rest of this paper is organized as follows: Section 2 gives in-depth information on time-series analysis in IoT and on image transformation. Section 3 presents image transformation techniques. A comprehensive literature review that uses time-

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[1] ScienceDirect [online], https://www.sciencedirect.com/, accessed [05/07/2024].

[2] IEEE Xplore [online], https://ieeexplore.ieee.org/Xplore/home.jsp, accessed [05/07/2024].

[3] Springer Link [online], https://link.springer.com/, accessed [05/07/2024].

series data in IoT applications is presented in Section 4. Section 5 outlines the challenges and future research directions. Lastly, Section 6 concludes the paper by emphasizing key important things.

2. Preliminaries

2.1. Time-Series Analysis in IoT

A time series is a sequence of data points collected at regular intervals over time, $X = \{(t_1, x_1), (t_2, x_2), ..., (t_n, x_n)\}$, where $x_i \in \mathbb{R}^m$, where n is the number of time-series data points and m is the vector dimension. The time series can be univariate or multivariate [17].

• Univariate Time-Series (UTS): If m equals 1, X is univariate. That means UTS includes a single variable observed over time.

• Multivariate Time-Series (MTS): If m is greater than 1, X is multivariate. In other words, multiple variables are observed over time in MTS.

For instance, a time series containing the daily average temperature of a city is represented as UTS, while a time series containing daily weather conditions (including temperature, moisture, and precipitation) for a city is represented as MTS. Although many real-world IoT systems have a large number of heterogeneous IoT sensors, there is more emphasis on UTS than MTS for several reasons. First, it is difficult to obtain the relationships between the variables in MTS correctly. Then, the fact that these variables have a high dimensionality poses a challenge when it comes to analyzing MTS data [18]. So, UTS is simpler and easier to implement than MTS. On the other hand, MTS is more complex and requires more data than UTS. However, MTS can be more accurate because it deals with relationships between different variables.

IoT time-series data is generated from different fields, including remote healthcare, wearable devices, energy management, smart buildings, transportation, etc. These time-series data are widely used in various IoT problems such as anomaly detection [19], monitoring systems [20], signal classification [21], fault diagnosis [22], maintenance prediction [23], etc. Figure 1 illustrates the details of the time-series analysis in IoT. Accordingly, time-series data are first generated by various sensors in IoT applications. These data are then transmitted to the cloud via network equipment and stored on cloud servers. Finally, they are analyzed for applications such as anomaly detection and maintenance prediction. IoT time-series data has several unique characteristics that distinguish it from other types of data and impact the analysis and interpretation of the data [24, 25]. First, with the advancements of 5G and beyond communication technologies, time-series data from IoT devices can be massive and high-dimensional, allowing for the simultaneous monitoring of billions of devices [26]. Secondly, IoT time series include both temporal correlations and complex spatial correlations. Thirdly, IoT time-series data can be prone to noise and missing values, which occur due to sensor failures, communication issues, data transmission problems, or errors in the measurements [27]. Lastly, IoT time-series data is often generated in real-time or near real-time.

Conventional time-series analysis techniques are not directly applicable due to the features of IoT time series data mentioned above. Understanding and leveraging these characteristics of IoT time-series data is essential for effective analysis, modeling, and decision-making in IoT applications. For instance, high dimensionality is required for scalability, which is an important challenge for IoT time-series analysis [28]. Also, since the data is continuously produced, real-time or streaming data processing methods are required to process data flow, perform instant analysis, and make timely decisions. Furthermore, noise and missing values can diminish data quality, necessitating the use of data cleaning and preprocessing techniques to ensure data integrity. To overcome these challenges, researchers have proposed different works. This paper focuses not only on the method but also on the change in the type of time-series data and the change in methods.
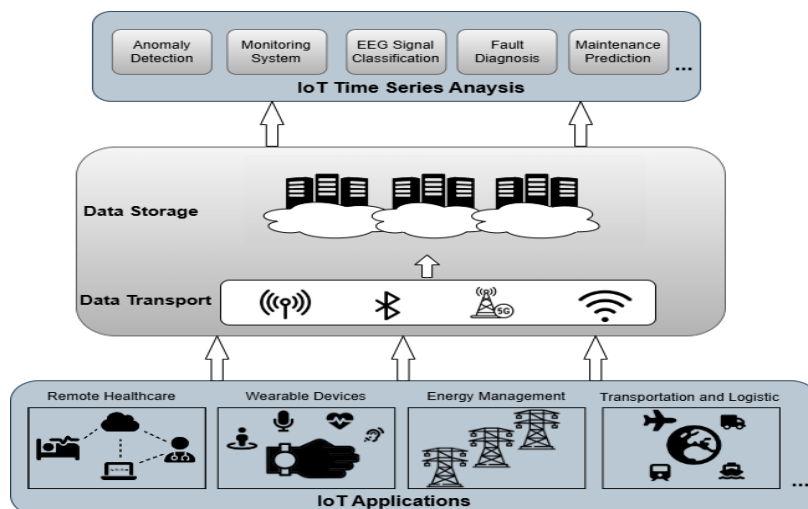

Figure 1. The general structure of time-series analysis in IoT

2.2. Image Transformation

Time-series image transformation converts time-series data into visual representations, such as images. It is a crucial process within the IoT context. This technique reduces IoT data dimensionality by compressing extensive data into a compact visual format, making it more successful at extracting key features and patterns from IoT time-series data. Additionally, it integrates seamlessly with deep learning algorithms like Convolutional Neural Network (CNN). These transformations enhance the analysis, interpretation, and utilization of time-series data in IoT applications. The transformation process of IoT time-series data into an image is illustrated in Figure 2.
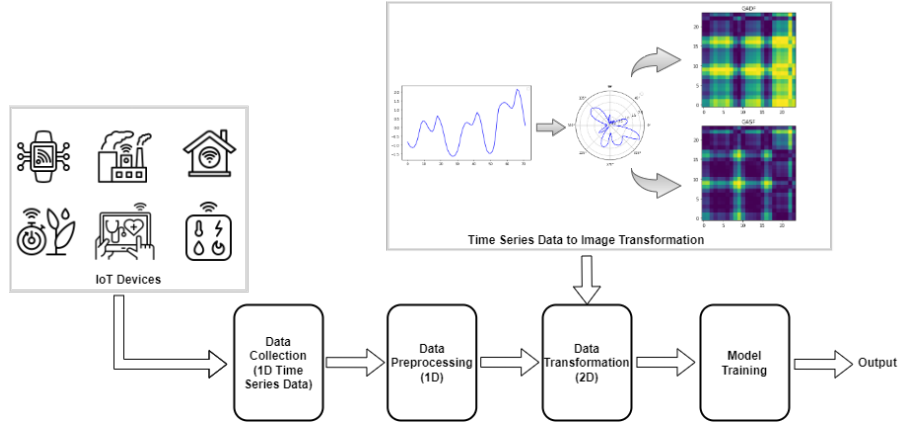

Figure 2. The overall framework of image transformation of IoT time-series data

There are varying image transformation techniques described in the literature. While these methods are directly applied to UTS, typically, they are not employed directly on MTS. To address this issue, some fusion methods are discussed in the literature. Image or feature fusion is a process that is proposed to merge the necessary information from images or features [29, 30]. When converting MTS data into two-dimensional (2D) images, fusion methods can be used to combine information from different variables or data sources to create a single image representation. One of the popular fusion techniques in literature is channel-based fusion, in which an RGB or multi-spectral channel image can be created by assigning each variable to a different color channel (e.g., red, green, blue) [31]. Also, some studies use tensor image fusion. MTS data is considered as a tensor and is analyzed by tensor decomposition techniques (e.g., Canonical Polyadic Decomposition) to extract patterns and interactions from the tensor data [32]. Lastly, feature level (early fusion) and decision level (late fusion) can be utilized to transform MTS [33]. Different variables are merged at the input stage and processed together with any methods at the feature level [34], [35]. On the other hand, each variable is converted into images separately, and then these images are combined at a later stage at the decision level [33], [36], [37]. Also, many researchers have used hybrid fusion by performing fusion in both decision and feature levels [38]. Table 2 summarizes the existing studies according to data types, such as univariate and multivariate. In addition, it emphasizes fusion techniques used in MTS data.

3. Time-Series to Image Transformation Techniques

There are several methods to transform one-dimensional (1D) time series into 2D images. Some of the popular techniques in literature are discussed below. Table 1 also shows the studies that used these methods.

3.1. Gramian Angular Field (GAF)

Given a time series is $X = \{x_1, x_2, \ldots, x_N\}$, including N samples, there are three steps to encode time series into images [76]. Firstly, X Time-series are scaled in the interval [0,1] according to Equation 1.

$$\tilde{x}_i = \frac{x_i - \min(X)}{\max(X) - \min(X)} \tag{1}$$

Then, the 1D time-series Cartesian coordinate system is transformed into a polar coordinate system, which is a new representation of the time series. Angular cosine (ϕ) and radius (r) are calculated to represent time series as polar coordinates using Equation 2.

$$\begin{cases} \phi & = \arccos(\tilde{x}_i), \quad -1 \leq \tilde{x}_i \leq 1, \quad \tilde{x}_i \in \tilde{X} \\ r & = \frac{t_i}{N}, \quad t_i \in \mathbb{N} \end{cases} \tag{2}$$

where t_i is the time stamp, and N is a constant factor in regularizing the span of the polar coordinate system. There are two types of GAF based on the sum/difference of the trigonometric function, which are the Gramian Angular Summation Field (GASF) and the Gramian Angular Difference Field (GADF). GASF is defined in Equations 3 and 4, and GADF is defined in Equations 5 and 6.

$$GASF = \begin{bmatrix} \cos(\phi_1 + \phi_1) & \cdots & \cos(\phi_1 + \phi_n) \\ \cos(\phi_2 + \phi_1) & \cdots & \cos(\phi_2 + \phi_n) \\ \vdots & \ddots & \vdots \\ \cos(\phi_n + \phi_1) & \cdots & \cos(\phi_n + \phi_n) \end{bmatrix} \tag{3}$$

$$GASF = \tilde{X}' \cdot \tilde{X} - \sqrt{I - \tilde{X}^2}' \cdot \sqrt{I - \tilde{X}^2} \tag{4}$$

$$GADF = \begin{bmatrix} \sin(\phi_1 - \phi_1) & \cdots & \sin(\phi_1 - \phi_n) \\ \sin(\phi_2 - \phi_1) & \cdots & \sin(\phi_2 - \phi_n) \\ \vdots & \ddots & \vdots \\ \sin(\phi_n - \phi_1) & \cdots & \sin(\phi_n - \phi_n) \end{bmatrix} \tag{5}$$

$$GADF = \sqrt{I - \tilde{X}^2}' \cdot \tilde{X} - \tilde{X}' \cdot \sqrt{I - \tilde{X}^2} \tag{6}$$

In the above equations, **I** refers to a unit row vector; $\tilde{X}'$ and $\sqrt{I - \tilde{X}^2}'$ is the transposed vector of the rescaled time series $\tilde{X}$ and $\sqrt{I - \tilde{X}^2}$, respectively.

Table 1. The Studies of Image Transformation Techniques for IoT

Reference	Year	Time-Series to Image Transformation Techniques						
		GAF	MTF	RP	STFT	CWT	HHT	Others
Baldini et al. [39]	2018			✓				
Yang et al. [40]	2019	✓	✓					
John et al. [41]	2019						✓	
Fahim et al. [42]	2020		✓					
Lyu et al. [43]	2020	✓						
Estabsari and Rajabi [44]	2020	✓	✓	✓				
Ferraro et al. [45]	2020	✓						
Xu et al. [46]	2020	✓						
Sreenivas et al. [47]	2021	✓	✓					
Zhu et al. [48]	2021	✓						
Anjana et al. [49]	2021				✓	✓	✓	
Zhou and Kan [32]	2021	✓						
Sharma et al. [50]	2021	✓						
Chen et al. [51]	2021				✓			
Jiang and Yen [52]	2021		✓					
Garcia et al. [53]	2021	✓	✓	✓	✓	✓		✓
Huang et al. [54]	2021	✓						
Jiang et al. [55]	2021	✓	✓					
Singh et al. [56]	2021				✓			
Santo et al. [57]	2022	✓	✓	✓		✓		
Chen and Wang [31]	2022	✓						
Bertalanič et al. [58]	2022	✓		✓				

Table 1. Continued: The Studies of Image Transformation Techniques for IoT

Alsalemi et al. [59]	2022	✓						
Zhang et al. [60]	2022			✓	✓			
Dou et al. [61]	2022					✓		
Abdel-Basse et al. [62]	2022	✓	✓	✓				
Wang et al. [63]	2022	✓	✓		✓			✓
Bai et al. [64]	2022	✓	✓					
Abidi et al. [65]	2023	✓	✓	✓				
Paula et al. [66]	2023	✓	✓	✓				
Quan et al. [67]	2023	✓	✓	✓				
Zhang et al. [68]	2023	✓						
Copiaco et al. [69]	2023							✓
Qu et al. [70]	2023	✓	✓					✓
Sun et al. [71]	2023	✓	✓					
Sayed et al. [72]	2023							✓
Hasan et al. [73]	2023	✓						
Hammoud et al. [74]	2023	✓	✓	✓				
Yan et al. [75]	2023	✓	✓		✓			

3.2. Markov Transition Fields (MTF)

MTF is a powerful tool that keeps time domain information in time-series data by representing the sequential Markov transition probabilities. By utilizing the Markov matrix of quantile bins, MTF offers an approach to converting the time-series data into images [76].

Given the time series $X = \{x_1, x_2, \ldots, x_n\}$, where x_i is the ith signal on the time-series. By determining Q quantile bins, each x_i is assigned to its corresponding bin $q_j (j \in [1, Q])$. In this way, a Markov transition matrix $\mathbf{W}$ in $Q \times Q$ Dimensions are obtained, which can be represented as:

$$W = \begin{bmatrix} w_{11} & w_{11} & \cdots & w_{1Q} \\ w_{21} & w_{22} & \cdots & w_{2Q} \\ \vdots & \vdots & \ddots & \vdots \\ w_{Q1} & w_{Q2} & \cdots & w_{QQ} \end{bmatrix} \tag{7}$$

$$w_{ij} = p\{x_t \in q_i | x_{t-1} \in q_j\} \tag{8}$$

where each element $w_{i,j}$ stands for the probability that a data point in the state q_j is followed by a data point in the state q_i. After normalization with $\sum_j w_{ij} = 1$, W becomes the Markov transition matrix. However, this matrix is insensitive to the distribution of X and temporal dependencies on time steps t_i. which results in the loss of excessive information in the process. To overcome this problem. W is expanded to a Markov transition field (MTF) matrix M by placing each probability in time order. It is expressed as below:

$$M = \begin{bmatrix} w_{ij|x_1 \in q_i, x_1 \in q_j} & \cdots & w_{ij|x_1 \in q_i, x_n \in q_j} \\ w_{ij|x_2 \in q_i, x_1 \in q_j} & \cdots & w_{ij|x_2 \in q_i, x_n \in q_j} \\ \vdots & \ddots & \vdots \\ w_{ij|x_n \in q_i, x_1 \in q_j} & \cdots & w_{ij|x_n \in q_i, x_n \in q_j} \end{bmatrix} \tag{9}$$

where M_{ij} in MTF represents the transition probability of data points in q_j followed by data points in q_j.

3.3. Recurrence Plot (RP)

RP is a widely used tool to visualize and analyze the recurrent behaviors of time series produced in a dynamic framework [77]. It is determined by a recursive matrix by computing the pairwise distance between the trajectories, in which the elements are calculated by Equation 10:

$$R_{i,j} = \Theta(\varepsilon - ||\vec{x}_i - \vec{x}_j||), i,j = 1, \dots, N \tag{10}$$

Where ϵ is a threshold, Θ is the Heaviside function used to binarize the distance matrices, where its value is zero for the negative argument and one for the positive argument.

RP exposes the local correlation information of a sequence and hidden patterns by computing the distance matrix between subsequences.

3.4. Short Time Fourier Transform (STFT)

STFT can be considered as the frequency domain representation of the original signal. It utilized a window function to extract a part of the time domain signal and then performed a Fourier transform on it to specify diverse signal properties [78]. The STFT of a given signal y(x) is calculated in Equation 11.

$$STFT(n, \omega) = \sum_{-\infty}^{\infty} y[x]\omega[n - x].e^{-j\omega n} \tag{11}$$

where $\omega(t)$ is the window function. In addition, the spectrogram is generated by squaring the STFT magnitude as follows:

$$Spectrogram(n, k) = |STFT(n, \omega)|^2 \tag{12}$$

Table 2. Summary of Image Transformation Application According to Data Types (U: Univariate, M: Multivariate)

Ref.	U	M	Year	Dataset	Gray/ Colored	Methods	Fusion Techniques
[68]	✓		2023	-Case Western Reserve University (CWRU) -Autonomous Experimental dataset	Color*	GASF GADF	-
[39]	✓		2018	- Private dataset of RF emissions collected from 11 IoT devices	Gray*	RP	-
[43]	✓		2020	- A private dataset that collected fiber intrusion disturbance signals	Color*	GAF	-
[48]	✓		2021	- KDD Cup 99 data	Color*	GAF	-
[58]	✓		2022	- Rutgers dataset	Gray Color	RP GAF	-
[42]	✓		2020	- REFIT electrical load measurement dataset	Color*	MTF	-
[44]	✓		2020	- Boston housing price data - Load Forecasting Dataset	Color*	RP GAF MTF	-
[41]	✓		2019	-Private dataset -Physionet/ Computing in Cardiology (CinC) Challenge 2016	Color*	HHT	-
[49]	✓		2021	- Seed	Color*	STFT CWT HHT	-
[51]	✓		2021	- Private dataset	Color*	STFT	-
[56]	✓		2021	- TUH Abnormal EEG Corpus	Color*	STFT	-
[60]	✓		2022	- Arrhythmia Data - Private dataset	Gray Color	RP STFT	-
[61]	✓		2022	- MIT-BIH arrhythmia - MIT-BIH normal sinus rhythm	Color*	CWT	-

Ref.	U	M	Year	Dataset	Gray/Colored	Methods	Fusion Techniques
				- BIDMC			
[66]	✓		2023	- Private dataset	Gray Color	GADF GASF MTF RP	

Table 2. Continued: Summary of Image Transformation Application According to Data Types (U: Univariate, M: Multivariate)

Ref.	U	M	Year	Dataset	Gray/Colored	Methods	Fusion Techniques
[52]	✓		2021	- Private dataset	Color*	MTF	-
[53]	✓		2021	- Airbus SAS Airbus SAS 2018	Gray Color	GAF MTF RP GS STFT DWT	-
[64]	✓		2022	- Private dataset	Color	GAF MTF	-
[73]	✓		2023	- WSN Dataset - ETDataset - TON IOT Dataset	Color*	GAF	-
[47]	✓		2021	- MIT-BIH arrhythmia database	Color	GAF MTF	-
[59]	✓		2022	- UK-DALE dataset	Color	GAF	-
[54]	✓		2021	- Caltrans Performance Management System (PeMS)	Color*	GASF	-
[46]	✓		2020	- WISDM - UCI HAR - OPPORTUNITY	Color	GASF GADF	-
[74]	✓		2023	- Private dataset - OpenEDS - NaveGaze	Gray Color	GASF GADF MTF RP	-
[75]	✓		2023	- CICIDS2018 - IoT-23 - N-BaIoT - WSCF20231 - Private Dataset	Color	GASF GADF WT	-
[31]		✓	2022	- PLAID - WHITED	Color	GAF	- Single-channel images correspond to three channels in the RGB Color space, respectively, to create an RGB image.
[32]		✓	2021	- 2018 China Physiological Signal Challenge (CPSC2018) - PhysioNet Long-term ST dataset	Color*	GADF	- Each channel of the ECG signal transforms into a GAF image, which is represented as a 2nd-order ECG tensor. - These images are then stacked together to form a 3rd-order ECG tensor by concatenating them along the 3rd dimension.
[45]		✓	2020	- Backblaze SMART dataset	Color*	GAF	- Each feature of the time series is transformed into a polar coordinate through the GAF.
[69]		✓	2023	- The Simulated Energy Dataset (SiD) - The Dutch Residential Energy Dataset (DRED)	Gray Color	a grayscale image an RGB color image	- A 5 × 5 matrix is used to organize features for a given instant. - Then, the matrix is resized to 28x28 pixels and saved as a Grayscale or an RGB Color image.

Ref.	U	M	Year	Dataset	Gray/Colored	Methods	Fusion Techniques
							(jet colormap)

Table 2. Continued: Summary of Image Transformation Application According to Data Types (U: Univariate, M: Multivariate)

Ref.	U	M	Year	Dataset	Gray/Colored	Methods	Fusion Techniques
[70]		✓	2023	- PLAID - WHITED - HRAD	Color*	MTF GAF WVI	- Each variable is converted into images using three encoding techniques. - Then, the WVI image and MTF image are superimposed to create two channels. Also, the I-GAF image is saved as a new image by the Energy-Normalization (EN) block. - Lastly, this image is superimposed with the other two images to get a three-channel image.
[50]		✓	2021	- 1D Biomedical Signals such as ECG, PPG, temperature, and accelerometer	Color	GAF	-The average of the computed features from various channels is found and provided as a single fused feature set using Channel-Wise Mean Fusion (CAF).
[62]		✓	2022	- UCI HHAR - UCI MEHEALTH	Color	RP MTF GAF	- Each row includes three measures, x, y, and z, for AM, GY, and MG data in 3D, respectively. - Converts x-, y-, and z-axis of signals as red, green, and blue channels of images.
[57]		✓	2022	- PAKDD2020 Alibaba AI OPS Competition - NASA bearings	Color*	RP GAF MTF STFT	- MTS encoded a set of feature maps that were computed with four different image transformation techniques.
[71]		✓	2023	- Private dataset	Color	GAF MTF	- GASF, GADF, and MTF layers are placed on the red, green, and blue layers, respectively, and saved images.
[65]		✓	2023	- SITS data, which was collected for a different study of the Dordogne-Reunion Island study - Koumbia	Color*	GADF GASF MTF RP	- Each UTS in MTS is flattened to the direct use of MTS instead of thinking independently of each UTS. - Then, generate the 2D images from the flattened MTS.
[72]		✓	2023	- Student Room Dataset (SRD) - UCI dataset (an office space) - Living Room Dataset (LRD)	Gray Color	data normalization matrix conversion	- The list of features(n) of the dataset is arranged into a 3xn matrix format. - Then, the matrix is resized to 28x28 pixels and saved as an image.
[83]		✓	2021	- Wafer dataset - ECG dataset	Color	GASF GADF MTF	- Encode MTS as a Colored image for each univariate time series. Each Colored image is separated into three monochromatic images, namely red, green, and blue (RGB). - After the separation, these monochrome images are

							concatenated together to form a huge image.

Table 2. Continued: Summary of Image Transformation Application According to Data Types (U: Univariate, M: Multivariate)

[63]	✓	✓	2022	- Case Western Reserve University (CWRU) Dataset - Society for Machinery Failure Prevention Technology (MFPT) Dataset	Color*	STFT The direct drawing method GADF MTF	- The vibration signals from multiple channels are combined into a 2D spectrum map.
[67]	✓	✓	2023	- Chinatown +84 UCR datasets	Color*	GAF MTF RP GMR	- 1D multi-scale features and 2D image features are fused in two distinct methods, covering the feature fusion methods such as SE and SA -Three images which are encoded with different coding methods are overlapped as three-channel data inputs.
[55]	✓	✓	2021	- 24 benchmark datasets (14 datasets for MTS and 10 dataset for UTS)	Color*	GAF MTF	- Each UTS in MTS is converted into GM images. Each variable is considered a channel. - G-image and M-image are concatenated GM feature maps by the adaptive feature aggregation, which pass through a corresponding shallow CNN separately.

* The color is not specified in the paper. For this reason, the color is determined based on the given images.

3.5. Continuous Wavelet Transformation (CWT)

CWT offers an unstable window size that adjusts based on the frequency at the cost of time resolution. Although STFT provides a great representation of the signal's time-frequency characteristics, it presents a fixed resolution in the frequency domain, which is not always ideal in certain scenarios. On the other hand, CWT is an operation linear on a time-domain signal y(t) given by:

$$W_{a,b}[y(t)] = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} y(t) * \phi\left(\frac{t-b}{a}\right) dt \tag{13}$$

where $\phi(\frac{t-b}{a})$ is a dilated version of the base wavelet function $\phi(t)$ by applying scaling and shifting. $a > 0$ is the scaling variable that regulates the spread of the function, and b is the time-shifting parameter or the instant of time at which the signal needs to be analyzed. The visual representation of the CWT of a signal is referred to as a scalogram [79].

3.6. Hilbert Huang Transform (HHT)

HHT is an analysis of signals that are non-stationary and non-linear [80]. While most techniques may fail in analyzing nonstationary and nonlinear systems, HHT alleviates the challenges of time-frequency-energy representation of the data. HHT includes two primary phases, called Empirical Mode Decomposition (EMD) and Hilbert Transform (HT). The transformation involves several processes. First, EMD is utilized to obtain Intrinsic Mode Functions (IMFs) from the signals. Second, the Hilbert transform is applied to each of the IMF components. Finally, the instant frequency and amplitude can be computed.

3.7. Other Transformation Methods

In addition to the aforementioned methods, the literature offers a range of alternative techniques that are commonly employed to address various types of problems. These methods play a pivotal role in the transformation of IoT time-series data. Some

of the notable approaches in this regard include data normalization combined with matrix conversion, the direct drawing method, Gaussian Mixture Regression (GMR), Gray-Scale encoding (GS), Gray-Scale image representations, RGB color image conversion, and the Wavelet Variance Image (WVI) method. These techniques have gained popularity within the literature for their effectiveness in transforming and enhancing the analysis of IoT time-series data.

Garcia et al. [53] proposed a modification of GS by choosing lower and upper bounds in the original formulations in accordance with the GAF encoding instead of minimum and maximum scaling. Wang et al. [63] used the direct drawing method which signals are transformed into a 2D spectrum map directly with plt functions in the Matplotlib package in Python without any processing. The direct drawing method has higher accuracy than GAF and MTF after STFT. The main idea of GS is to transform time-domain raw signals into images. The time-domain raw signals complete the pixels of the image sequentially. Wen et al. [81] reorganized the GS using CNN for fault diagnosis in manufacturing systems. A transformation method consisting of data normalization and matrix conversion was used for 2D image representation [72], [69]. 1D time-series data is first normalized in [0,1] with n features. Then, these features are arranged in *mxm* matrix format. Lastly, this matrix is resized to 28x28 pixels and saved as an image to obtain a gray-scale image or RGB color image. The Voltage–Current (VI) trajectory can be converted into a pixelated VI image (*nxn* matrix) by meshing the VI trajectory [82]. Qu et al. [70] generated 2D load signatures according to the corresponding features of the signal based on the Weighted Voltage–Current (WVI) trajectory image.

4. Image Transformation in IoT Applications

IoT encompasses various domains where time-series data is frequently used. Time-series data is a data type that includes a sequence of data points that are collected at regular intervals over time. Table 3 summarizes the existing studies by categorizing them according to nine IoT domains. Here are some IoT domains where time-series data is commonly utilized.

4.1. Security and Privacy

The security and privacy domain within IoT focuses on handling the challenges and risks associated with ensuring the confidentiality, integrity, availability, and privacy of IoT systems, devices, and data. Security in the IoT domain includes implementation of preventive measures to obstruct unauthorized access, data breaches, and malicious activities that have the potential to jeopardize the functionality, integrity, and confidentiality of IoT devices and systems. Privacy in the IoT domain refers to the protection of individual's personal information and their control over how it is collected, used, and shared by IoT systems.

IoT time-series data plays a significant role in the security and privacy domain by providing valuable insights into the behavior, patterns, and anomalies within IoT systems. Anonymization, encryption, and access controls should be applied appropriately to protect sensitive information contained within the time-series data. In the context of IoT security and privacy, time-series data can be leveraged for various purposes: Intrusion detection, unauthorized access detection, anomaly detection, security analytics prediction, etc.

Baldini et al. [39] presented an approach for the authentication of IoT wireless devices based on Radio Frequency (RF) emissions. The proposed approach, which combines CNN and RP (RP-CNN), is tested on the RF emissions dataset, which is experimental data collected from 11 IoT devices. They also applied two classification methods called T-CNN, which utilizes the digital representation of the RF emissions directly with CNN, and FEAT, which extracts the statistical characteristics of RF emissions from their digital representations. The results showed that the RP-CNN improves accuracy when compared to T-CNN and FEAT. Lyu et al. [43] proposed an intrusion pattern recognition framework. The method, based on the GAF and CNN, achieved a high-speed response time of 0.58 s and a high recognition accuracy of 97.57% for six types of optical fiber intrusion events. In addition, it improved the robustness and practicability of the system because the GAF algorithm is not sensitive to the fluctuation of power sources in the optical path. Zhu et al. [48] developed a monitoring system to detect abnormal traffic and vulnerability attacks in IoT applications. In the system, time series data was converted into GAF graphs, and the CNN and Long Short-term Memory (LSTM) combination model was utilized to monitor traffic. However, the system that combined C5.0 decision tree (DT) and time series analysis introduced a novel idea for the traffic analysis of IoT devices. Bertalanič et al. [58] proposed a new resource-aware approach based on image transformation and deep learning for anomaly detection in the wireless link layer. Time-series data were transformed into images using RP and GAF. The experiments show that RP outperforms the GAF methods by up to 14%. Yan et al. [75] developed an intrusion detection model for few-shot attacks. 1D network traffic data was converted into three-channel RGB images using GADF, GASF, and WT. The three two-dimensional images are fused into the red, green, and blue channels of one RGB image, respectively. Additionally, the data augmentation module uses an improved Denoising Diffusion Probabilistic Model (DDPM), and the image classification module employs a variable network ETNet V2 based on EfficientNetV2. The results indicate that the proposed improved GAF method, combined with WT, achieves the highest accuracy compared to one-dimensional data and other types of conversion methods such as GAF, MTF, and STFT.

4.2. Energy Management

IoT enables the monitoring and control of energy consumption, smart grid management, and the integration of renewable energy sources. It helps optimize energy distribution, reduce waste, and improve sustainability.

Fahim et al. [42] proposed a model called Time-series to Image (TSI) to detect abnormal energy consumption in residential buildings. This study focused on analyzing the univariate time-series energy data for very short-term analysis. The Proposed model utilized a One-Class Support Vector Machine (OCSVM) as a classifier and MTF as a converter, which transforms univariate time-series data into images. In this work, the authors demonstrated that this image representation further enhances the classifier's ability to detect anomalous behavior more efficiently. Estebsari and Rajabi [44] proposed a hybrid model based on CNN and image encoding methods for single residential loads. They applied three different image encoding methods, including the RP, GAF, and MTF, to historical load time-series data. The experiments revealed that RP performed the best among the three encoding methods. Alsalemi et al. [59] developed a novel GAF classifier based on the EfficientNet-B0 for the classification of edge internet of energy applications. The authors aimed to introduce the first lightweight classifier for 2D energy consumption working on the ODROID-XU4 platform.

Copiaco et al. [69] proposed a 2D pre-trained CNN model for detecting anomalies in building energy consumption. This model used the 2D versions of the energy time-series signals to give input to several pre-trained models, such as AlexNet and GoogleNet, as features of the Linear Support Vector Machine (SVM) classifier. In this study, 1D time series were transformed into Grayscale and Jet Color image representations. This study showed that converting energy time-series data into images can provide an increase in the correlation between images with the same class. Chen and Wang [31] proposed an edge-computing architecture for load recognition tasks in the field of Non-Intrusive Load Monitoring (NILM) that reduces data transmission volume and network bandwidth requirements. They also developed a color encoding method based on GAF to construct load signatures in home appliances. Qu et al. [70] constructed three 2D load signatures based on the WVI, MTF, and current spectral sequence-based GAF (I-GAF). Additionally, they designed a new Residual Convolutional Neural Network with Squeeze-and-Excitation (SE) and Energy-Normalization (EN) blocks (EN SE-RECNN) for appliance identification in NILM. This study compared the performance of various models, including Residual Convolutional Neural Network (RECNN), Residual Convolutional Neural Network with EN blocks (EN-RECNN), and EN-SE-RECNN, and confirmed that the performance of EN-SE-RECNN was better. Also, their findings demonstrate that the fusion of different signatures enhances performance by enriching the information related to appliance identification.

4.3. Healthcare

In healthcare applications, time-series data assists in monitoring patient vital signs, analyzing health trends, predicting disease outbreaks, and optimizing healthcare resource allocation. Zhou and Kan [32] developed a tensor-based framework for ECG anomaly detection in Internet of Health Things (IoHT)-based cardiac monitoring and smart management of cardiac health. The multi-channel ECG signals were converted into 2D images using GADF. In this study, a tensor decomposition-unsupervised anomaly detection model has been proposed, utilizing multi-linear principal component analysis (MPCA) and deep support vector data description (deep SVDD). The proposed model demonstrated that the framework using 2D image representations shows better performance than one that directly uses 1D signals because of the difficulty of extracting hidden information. Also, when the effect of the ECG length on the GADF image was examined, larger GADF images were found to give higher accuracy, as well as the area under the ROC curve (AUROC) and F-score.

Sreenivas et al. [47] proposed a CNN model for the classification of arrhythmia in dual-channel ECG signals. In this study, GAF and MTF were used to convert the ECG time-series signals into images. The result showed that the GAF model achieved higher accuracy compared to the MTF. Anjana et al. [49] proposed a CNN model based on various types of image encoding approaches to classify human emotions using EEG signals. In this study, Spectrogram, Scalogram, and HHT were employed to transform EEG signal data into images. The experiments showed that the scalogram of image encoding provides the best classification accuracy. Paula et al. [66] proposed a 2D-kernel-based CNN architecture to classify the Steady State Visually Evoked Potentials (SSVEP) signal. In this work, EEG data is encoded into images using GADF, GASF, MTF, and RP. This study demonstrated that the GADF and RP methods consistently showed higher performance. Also, the 1D-kernel-based structure of the model was insufficient for learning the necessary information from the data.

John et al. [41] developed a cardiac monitoring system based on wireless sensing, aiming for accurate diagnosis of heart diseases. The system used MQTT for long-distance transmission and HHT for preprocessing and feature extraction of the data. Sharma et al. [50] introduced a patient monitoring system based on ontology for early remote detection of COVID-19. The proposed system relied on an alarm-enabled bio-wearable sensor system that utilized sensory 1D biomedical signals such as ECG, PPG, temperature, and accelerometer. These 1D Biomedical signals were converted into images with GASF after extracting their features. Then, SVM and K-Nearest Neighbors (KNN) were employed as ML-based classifiers for the classification of COVID-19 patients. Chen et al. [51] proposed an indoor speed estimation framework, SpeedNet, from radio signals, mainly aimed at monitoring the movement of elderly individuals. The SpeedNet framework includes three modules: the dominant path extraction module, the spectrum analysis module, and the deep learning module. The dominant path signal which is obtained from the extraction module was analyzed using STFT in the spectrum analysis module. Also, CNN and LSTM were utilized in the deep learning module to extract spatial and temporal features. They introduced a new approach for contactless indoor speed estimation with radio signals, addressing the challenges posed by the complex relationship between the speed of moving individuals and radio signals. Singh et al. [56] suggested a brain signal classification model that transformed brain signals into images as input for a pre-trained VGG19 model by using STFT for seizure detection. In addition, blockchain technology was utilized to store images more securely. The study also emphasizes the importance of

selecting an appropriate encoding method, which involves using different image conversion techniques such as spectrograms, chronograms, or kurtograms. Zhang et al. [60] proposed a system based on 5G-enabled Medical IoT for automatic detection of arrhythmia (ARR). Time-frequency spectrograms obtained from RR interval sequences using RP and Fourier Transform (FT) were used as inputs to a unified CNN and LSTM model for the classification of ECG signals. Dou et al. [61] proposed a novel classification method based on CWT and CNN within the context of the IoT domain. Their approach simultaneously classifies various ECG signals for heart disease diagnosis using GoogleNet. Besides, ECG signals were converted into time-frequency images with CWT. Abdel-Basset et al. [62] developed a lightweight Human Activity Recognition (HAR) architecture designed to classify human activities captured by heterogeneous sensors from different IoT devices. They proposed a few modifications for three encoding techniques, including RP, MTF, and GAF. These techniques encode the three-dimensional (3D) time-series data of human activities into three-channel images to overcome the heterogeneity in sensory data.

Hammoud et al. [74] proposed a DL framework for the classification of Parkinson's disease (PD) and Progressive Supranuclear Palsy (PSP). They extracted the pupil features such as coordinates, area, minor axis, and major axis. The time-series signals represented by the pupil's coordinates and its area were reprocessed. Then, these features were converted into images using GASF, GADF, MTF, RP, RGB-GAF, and GAF-MTF. The results demonstrate that GADF, RP, and RGB-GAF achieved higher accuracy than other methods.

4.4. Industrial

Industrial IoT (IIoT) involves connecting industrial equipment, machinery, and systems to enable data monitoring, analysis, and optimization in manufacturing, energy transportation, and other industrial sectors. In industrial settings, time-series data helps monitor equipment performance, predict failures, optimize maintenance schedules, and improve overall operational efficiency.

Various image encoding methods are commonly used in IIoT to provide intelligent and efficient fault diagnosis. Wang et al. [63] proposed a framework for fault diagnosis of single-channel and multi-channel bearing signals. They combined spectrum map information fusion and CNN to achieve fast fault diagnosis. GADF, MTF, and STFT were used to generate a 2D spectrum graph from 1D bearing vibration data, and STFT achieved the best result with the lowest loss value. The experiments indicated that the STFT method could use multichannel information effectively and improve fault identification accuracy. Similarly, Zhang et al. [68] presented a novel fault diagnosis method that combines GAF, Extreme Learning Machine (ELM), and CNN. They explored different encoding methods, including GADF, GASF, spectrogram, and gray-scale image, to indicate the effectiveness of the chosen encoding techniques for pattern recognition. The findings indicated that the GADF has the highest performance. Santo et al. [57] developed a model that combined time-series encoding techniques and CNN for predictive maintenance. This paper evaluated four main encoding techniques, RP, GAF, MTF, and Wavelet transform. The RP achieved the best performance in all metrics.

Ferraro et al. [45] developed an efficient method for predictive maintenance that improved maintenance strategies and decreased downtime and cost. The method involves transforming temporal time-series data into images using GAF and utilizing deep learning strategies to predict the health status of the Hard Disk Drive (HDD). Jiang et al. [52] proposed the MTF-CLSTM method, which combines the MTF, CNN, and LSTM to predict product quality in Wire Electrical Discharge Machining (WEDM). MTF is employed to transform dynamic WEDM manufacturing conditions into images. In addition, features were extracted from the images with CNN, and LSTM was used to predict the surface roughness of the WEDM products right after manufacturing. When the MTF-CLSTM method was compared with the Deep Neural Network (DNN) and the Markov Chain DNN(MC-DNN) methods [84], the proposed method achieved the best performance.

Garcia et al. [53] explored six encoding methods (GAF, MTF, RP, GS, spectrogram, and scalogram) and the modifications to enhance their robustness against the variability in large datasets when transforming temporal signals into images. This study revealed that different encoding methods exhibit competitive results for anomaly detection in large datasets. Bai et al. [64] proposed a fault diagnosis method called Time-series Conversion-DCGAN (TSC-DCGAN). They utilized GAF and MTF to transform 1D electrical parameters into 2D images. Additionally, the Deep Convolutional Generative Adversarial Network (DCGAN) was used as a generation method to handle the inadequate data samples of electrical parameters from oil wells. Also, the experimental results show that GAF images performed better in terms of classification effectiveness compared to MTF images. Sun et al. [71] put forward an idea for diagnosing composite failures of the adaptable multi-sensor bearing gear system by leveraging GAF, MTF, and ResNet. The complicated multi-dimensional time-series signals were fused and transformed into 2D images to facilitate classification tasks using GAF and MTF.

4.5. Environmental Monitoring

IoT devices are exploited to monitor and manage environmental conditions such as air quality, water quality, pollution levels, and natural resource conservation. These solutions aid in environmental protection and sustainable practices.

Abidi et al. [65] proposed a framework for the classification of Land Use/Land Cover (LULC) mapping based on 2D encoded multivariate Satellite Image Time-series (SITS). In this work, multivariate SITS data were converted into 2D images by

GADF, GASF, MTF, and RP. The results indicated that the RP technique performed better than all encoding techniques. In addition, the combination of 2D encoding techniques achieved better performance than using the encoding methods alone.

4.6. Smart Building

Smart Building enhances occupant comfort, reduces energy consumption, improves safety and security, and optimizes building operations and maintenance. Time-series data in smart buildings is employed to monitor and control various building systems, such as HVAC (Heating, Ventilation, and Air Conditioning), lighting, and occupancy.

Sayed et al. [72] presented an approach for the detection of occupancy using environmental sensor data such as temperature, humidity, and light sensors. In this study, multivariate time-series data were transformed into gray-scale and RGB images using an image transformation method to encode better and obtain relevant features. This method covered data normalization and matrix conversion, unlike commonly used methods such as GAF. The results showed that gray-scale images provide the appropriate balance between accuracy and training time compared to the colored images.

4.7. Transportation and Logistics

IoT applications in transportation and logistics include fleet management, vehicle tracking, route optimization, cargo monitoring, and driver safety. These applications have the potential to transform the industry by enabling intelligent decision-making, reducing costs, and improving customer experience.

Huang et al. [54] developed a new method, namely the Traffic Sensor Data Imputation GAN (TSDI GAN), for missing data reconstruction. GASF was employed in the paper to process time-series traffic data and transform it into an image format for missing value imputation using CNN.

4.8. Wearable Devices

Wearable devices focus on the integration of technology into portable devices that individuals can wear. These devices are equipped with sensors, connectivity capabilities, and computing power, enabling them to collect data, interact with the environment, and provide personalized experiences.

Wearable devices incorporate various sensors to collect data about the user and their environment, such as accelerometers, heart rate monitors, GPS, temperature sensors, etc. They are also connected to other devices or networks through wireless technologies such as Bluetooth and Wi-Fi. Thus, wearable devices offer individuals convenient access to personalized data and experiences, empowering them to monitor their health, improve their fitness, and stay connected in a more seamless and unobtrusive manner.

With the advancement of the IoT and wearable devices, sensor-based HAR has gained importance due to convenience and privacy characteristics. Xu et al. [46] presented two improvements based on GAF and deep CNN based on the Multi-dilated Kernel Residual (Mdk-Res) module for HAR. The findings indicated that the developed model was able to efficiently extract multi-scale features and improve the accuracy of activity recognition by utilizing the GAF algorithm's characteristics, along with the structure and advantages of CNN, residual learning, and dilated convolution.

Table 3: Summary of Image Transformation Techniques Studies in IoT Application Domain (A: Authentication, C: Classification, D: Detection, I: Imputation, P: Prediction, R: Recognition)

Domain	Ref.	Year	Problem Type	Application Type	Methods	Models	Comparison Models	Results
Security	[39]	2018	A	Authentication of IoT devices	RP	CNN	T-CNN FEAT	*Accuracy:* RP-CNN: 96.8% T-CNN: 96.2% FEAT: 91.3%
	[43]	2020	C	Intrusion Pattern Recognition	GAF	CNN	VGG16 ResNet50 Inception V3	*Accuracy:* 97.67%
	[48]	2021	C	Anomaly Detection	GAF	C5.0 DT CNN-LSTM	-	*Accuracy:* 96%
	[58]	2022	C	Anomaly Detection	RP GAF	CNN	KNN SVM AlexNet VGG11	*F1-score:* SuddenD: 1.00 SuddenR: 1.00 InstaD: 0.92 SlowD: 0.99 No anomaly: 0.99

	[75]	2023	C	Intrusion Detection	GADF GASF WT	DDPM ETNet V2	CNN SVM	*Accuracy:* 99.20%

Table 3. Continued: Summary of Image Transformation Techniques Studies in IoT Application Domain (A: Authentication, C: Classification, D: Detection, I: Imputation, P: Prediction, R: Recognition

	[42]	2020	D	Anomaly Detection	MTF	OCSVM	PCA+OCSVM	*F1-score:* 88%
	[44]	2020	P	Single Residential Load Forecasting	RP GAF MTF	CNN	SVM ANN 1D-CNN	*MAE:* 0.59 *MAPE:* 12.54 *RMSE:* 0.79
	[59]	2022	C	Energy Consumption Data Classification	GAF	EfficientNet-B0	-	-
Energy Management	[31]	2022	R	Load Recognition	GAF	ResNet	Other Ref. Papers (LSTM, CNN and three AlexNet versions)	*Accuracy:* PLAID:97.97% WHITED:97.90%
	[69]	2023	D	Anomaly Detection	Grayscale image RGB color image (jet colormap)	AlexNet GoogleNet SqueezeNet Linear SVM	AlexNet GoogleNet	*F1-scores:* SiD: 93.63% DRED: 99.89% *Accuracy:* SiD: 96.11% DRED: 99.91%
	[70]	2023	R	Load Recognition	MTF GAF WVI	EN-SE-RECNN	RECNN EN-RECNN EN-SE-RECNN	*Accuracy:* PLAID:97.43% WHITED:95.99% HRAD:98.14%
	[41]	2019	C	Cardiac Monitoring System	HHT	Adaptive Threshold Method	-	*Accuracy:* 96%
	[47]	2021	C	Arrhythmia Classification	GAF MTF	CNN	Other Papers	*Accuracy:* GAF: 97% MTF: 85%
	[51]	2021	P	Indoor Speed Estimation	STFT	CNN-LSTM	Other Papers	*Accuracy*: 96.33%
	[32]	2021	D	Anomaly Detection	GADF	Deep SVDD Statistical Control Charts MPCA	Adaboost SVM	*F1-score:* Atrial fibrillation: 0.9771 Right bundle branch block: 0.9986 ST-depression: 0.9550
Healthcare	[50]	2021	D	Remote Patient Monitoring (RPM)	GAF	SVM KNN	SVM and KNN with different Fusion Methods	*Accuracy:* 96.33%
	[49]	2021	C	Emotion Classification	STFT CWT HHT	CNN	-	*Accuracy:* Scalogram: 98%, Spectrogram: 78%, HHT: 75%
	[56]	2021	C	Brain Signal Classification	STFT	VGG-16	SVM Logistic Regression Random Forest	*Accuracy:* 88.04%
	[60]	2022	C	ECG Signal Classification	RP FT	CNN-LSTM	Other Papers	*Accuracy:* 99.06%, *Sensitivity:* 98.29%, *Specificity:* 99.73%

| | [62] | 2022 | C | HAR | RP MTF GAF | CNN-based model | Other Papers | *Accuracy:* HHAR: 98.90%, MEHEALTH: 99.68% |

Table 3. Continued: Summary of Image Transformation Techniques Studies in IoT Application Domain (A: Authentication, C: Classification, D: Detection, I: Imputation, P: Prediction, R: Recognition

Domain	Ref.	Year	Problem Type	Application Type	Methods	Models	Comparison Models	Results
Healthcare	[61]	2022	C	ECG Signal Classification	CWT	GoogLeNet	AlexNet VGGNet	*Accuracy:* 94.28%
	[66]	2023	C	EEG Signal Classification	GADF GASF MTF RP	ImageNet DenseNet ResNet Google Net AlexNet	1D-kernel-based CNNs	*Accuracy:*(ResNet50) RP –> 96% GADF –> 94% MTF –> 88% GASF –> 54%
	[74]	2023	C	Neurological Diseases Diagnosis	GADF GASF MTF RP	CNN	Other Papers	*Accuracy:* Left eye: 96.9% Right eye: 90.8% Both eyes: 96.9%
Industrial	[45]	2020	P	Maintenance Prediction	GAF	CNN	LSTM	Accuracy: 97.70%
	[52]	2021	P	Product Quality Prediction	MTF	CNNLSTM	Other Papers DNN MC-DNN	*MAPE:* 3-state MTF: 3.11% 4-state MTF: 2.94% 5-state MTF: 3.24%
	[53]	2021	D	Anomaly Detection	GAF MTF RP GS STFT DWT	CNN	-	*AUC:* SC: 92 GS: 89 MTF Mod: 87 GAF Mod: 84
	[57]	2022	P	Maintenance Prediction	RP GAF MTF CWT	CNN	LSTM GRU XGBoost ResNet-50 DenseNet-121 VGG-16	*F1-score:* GAN: 34.47 CNN: 59.24 *Accuracy:* RP: 0.95
	[63]	2022	D	Bearing Fault Detection	STFT The direct drawing method GADF MTF	VGG	-	*Accuracy:* MFPT: STFT: 99.8% CWRU: DDM: 93.8% GADF: 78.1% MTF: 79.7% STFT: 100%
	[64]	2022	D	Fault Diagnosis	GAF MTF	DCGAN EfficientNet	CNN VGG16 GoogleNet	*Accuracy:* 0.8541
	[71]	2023	D	Fault Diagnosis	GAF MTF	ResNet	DCNN	*Accuracy:* 72.14%

| | [68] | 2023 | D | Fault Diagnosis | GASF GADF | ELM CNN | AlexNet ANN SVM KNN | *Accuracy:* 99.2% |

Table 3. Continued: Summary of Image Transformation Techniques Studies in IoT Application Domain (A: Authentication, C: Classification, D: Detection, I: Imputation, P: Prediction, R: Recognition

Domain	Ref.	Year	Problem Type	Application Type	Methods	Models	Comparison Models	Results
Environmental Monitoring	[65]	2023	C	Time-series Classification	GADF GASF MTF RP	CNN ResNet-50	Other Papers	*F1-scores:* Reunion Island:89.34% Dordogne:90.26% Koumbia study: 78.94%
Smart Building	[72]	2023	P	Building Occupancy Prediction	Data Normalization Matrix Conversion	CNN	KNN DT RF	*Accuracy:* SRD: 99.11% LRD: 98.54% UCI: 99.42%
Transportation and Logistics	[54]	2021	I	Traffic Data Imputation	GASF	DCGAN	Other Papers	*MAE:* 13.7%
Wearable Devices	[46]	2020	C	HAR	GASF GADF	Mdk-Res Module ResNet	Multilayer Perceptron (MLP) LSTM CNN_1D CNN_2D ResNet GoogleNet	*Accuracy:* Proposed: 96.83% CNN: 93.23 LSTM: 87.53
Others *	[40]	2019	C	Time-series Classification	GASF GADF MTF	ConvNet	ConvNet VGG16 Other Papers	*Error rates:* MTF: 0.4 (Wafer) GADF: 5.35 (ECG)
	[55]	2021	C	Time-series Classification	GAF MTF	ADDN	ResNet Encoder MLP MCDCNN Time-CNN	*MPCE:* UTS: 2.90 MTS: 4.00
	[67]	2023	C	Time-series Classification	GAF MTF RP GMR	ResNet	ResNet Dynamic Time Warping (DTW) MLP Fully Convolutional Network (FCN)	*Error rates:* GMR: 0.2305 GAF: 0.2431 MTF: 0.2863 RP: 0.2543
	[73]	2023	D	Sensor Fault Diagnosis	GAF	ResNet18-SVM-GAN	ResNet18-SVM	*Accuracy:* 98.7%

* The studies have not been provided with any domain-specific information

4.9. Others

Beyond the above-mentioned IoT domains, various studies employ data from different fields within IoT. In these studies, the effects of the proposed methods on the datasets obtained from diverse fields were examined. For example, Yang et al. [40] used two well-known MTS datasets, Wafer and ECG, to classify 1D signals. MTS data was transformed into 2D images by applying GASF, GADF, and MTF. These images were then concatenated as RGB input channels for the ConvNet classification model. The study concluded that the choice of encoding methods had no significant impact on the prediction results. Jiang et al. [55] evaluated the Adaptive Dila-DenseNet (ADDN) model for classifying UTS and MTS data across 24 benchmark IoT datasets. Both UTS and MTS data were converted into GM-images by leveraging GAF and MTF methods to feed into the ADDN model. Quan et al. [67] investigated the impact of different feature construction and fusion methods on time-series classification results. They proposed an improved Multi-Scale ResNet (MSResNet) for time-series classification. In this study, three images encoded with different methods, including GAF, MTF, and RP, were superimposed as three-channel data inputs as GMR images. Besides, 1D multi-scale features and 2D image features were fused using two distinct methods, including Squeeze-and-Excitation (SE) and Self-Attention (SA) feature fusion architectures. Hasan et al. [73] introduced a sensor fault detection approach based on digital twins. They used the GAN method to create the digital representation of the sensor. Also, the GAN was trained with images obtained by converting time-series using GAF.

5. Research Challenges and Future Directions

Converting time-series data into images attracted significant attention in facilitating IoT data analysis. While this transformation can offer new perspectives and enable advanced image processing techniques, it also introduces several challenges and limitations related to data handling, computational requirements, interpretability, and real-time processing. Since IoT devices typically generate large volumes of data, converting this data into images can result in significant storage and processing expenses. Additionally, time-series data often contains noise and anomalies, which can negatively impact the transformation process and the quality of the resulting images. To address this issue, significant preprocessing may be required to clean and normalize the data before transformation, adding to the complexity and time required for analysis. Also, the transformation process is not simple and requires complex techniques. The choice of the conversion method can significantly affect the result and the quality of the resulting images. However, these images may not be easily interpreted by users who are not familiar with certain transformation techniques. Lastly, some machine learning and image processing algorithms may not be appropriate for analyzing images derived from time-series data, as they cannot adequately describe the underlying patterns or relationships.

As mentioned above, this transformation process has a set of challenges. The major challenges and potential solutions are presented to address them as follows for researchers [44, 85–96].

• IoT time-series data is often prone to noise and missing values caused by sensor failures or network problems, which can adversely affect the image quality. Also, missing data when creating an image can lead to incomplete representations. To address this challenge, researchers should investigate advanced imputation techniques to handle missing gaps. This could involve developing specialized image inpainting models [85] specifically designed for images derived from time-series data or implementing GAN-based models [86] that can be utilized to learn the unique temporal patterns associated with various IoT domains.

• Encoding large-scale IoT time-series data can be computationally expensive and memory-intensive. To overcome this limitation, future research should develop dynamic resolution techniques that automatically determine optimal image dimensions based on data complexity [88]. On the other hand, it should be noted that very small sizes can lead to the loss of essential details while reducing memory and computational costs. Moreover, current techniques can be redesigned to accelerate image conversion.

• The process of transforming time-series data into images involves compressing the temporal information into a 2D representation. This compression can cause information loss. Balancing the trade-off between dimensional reduction and information loss is a critical challenge in this field [89]. To minimize information loss, researchers should focus on developing robust transformation techniques that balance dimensionality reduction and information preservation. Besides, in order to avoid information loss, modifications can be made to the transformation methods, such as changing the function in a formula [90], [91].

• IoT time-series data can involve multiple variables or sensors, resulting in MTS. However, the methods described cannot be applied directly to MTS. To better handle multivariate data, researchers should focus on various approaches. They can develop specialized encoding techniques that can directly represent relationships between variables, adapting MTS data in the visual domain. In addition, dimension reduction methods can be utilized to implement encoding techniques directly [92, 93] that preserve variable correlations while reducing complexity. Also, effective fusion techniques where each channel captures different aspects of the multivariate relationship can be developed to transform MTS data [94].

• Real-time or near-real-time image representations for dynamic IoT environments can be challenging [44]. If the image transformation process takes longer than the time between intervals, the system can fail eventually.

This delay may be unacceptable for decision-making systems within a short period in IoT applications such as IIoT and smart

cities. To improve processing speed, future research should increase hardware resources that can help reduce computation time. Also, edge devices provide prominent computational resources for faster real-time decision-making [95], where different levels of transformation happen at different nodes. Furthermore, combining edge and cloud architecture in IoT can effectively address network traffic congestion and latency concerns [96].

6. Conclusion

In recent years, the transformation of time-series data into images has become widespread. However, the adoption of these techniques in IoT domains is still in its early stages, with expectations for them to become commonplace across most IoT domains in the near future. This study presents a comprehensive review of image transformation techniques employed in various IoT domains, including smart buildings, industrial settings, energy management, healthcare, security, and more. We categorize existing studies based on their encoding techniques, IoT application areas, and data types. In the literature, various transformation techniques are applied to both UTS and MTS IoT data. These transformation techniques are typically used in conjunction with fusion techniques for multivariate time-series IoT data. Among the techniques employed, GAF and MTF are the most commonly used image transformation techniques, particularly in domains such as energy management, healthcare, and industrial applications with purposes such as anomaly detection, fault diagnosis, and time-series classification. It is crucial to choose the right method that is suitable for the specific problem and dataset. This decision can significantly impact the result and the quality of the resulting images. In addition, handling some important issues such as noise, missing values, and outliers increases the effectiveness of the converted images. Additionally, this paper discusses the associated challenges, weaknesses, limitations, open issues, and future research directions.

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Author(s) Contributions

This article was prepared by multiple authors. The contributions of each author are as follows:

Duygu Altunkaya contributed to the conception and design of the study, data analysis and interpretation, writing the technical sections of the paper, critically reviewed its content, and literature review. Feyza Yıldırım Okay contributed to the conception and design of the study, writing the technical sections of the paper, critically reviewed its content, and the literature review. Suat Özdemir contributed to the overall coordination, the conception and design of the study, critically reviewed the manuscript's content and the literature review.

Conflict of Interest Notice

The authors declare that there is no conflict of interest regarding the publication of this paper.

Ethical Approval and Informed Consent

It is declared that during the preparation process of this study, scientific and ethical principles were followed, and all the studies benefited from are stated in the bibliography.

Availability of data and material

Not applicable

Artificial Intelligence Statement

ChatGPT was used solely for grammar and spelling corrections during the preparation of the article. The scientific content, analysis, and interpretation were produced entirely by the authors.

Plagiarism Statement

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