SC-β-VAE-GAN: A SHIFT CORRECTION VAE-GAN MODEL FOR IMPUTATION AND AUGMENTATION OF HANDWRITING MULTIVARIATE TIME SERIES DATA

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by

Alpapara, Nichole
Lagatuz, John Patrick
Peroche, John Mark
Torreda, Kurt Denver

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Chapter 1

THE PROBLEM AND ITS SETTING

Introduction

The application of deep learning models has seen remarkable success across various fields, such as healthcare, climate science, industrial automation, and emotional state recognition. However, these fields often struggle with limited data availability, as acquiring well-annotated data is both expensive and time-consuming (Pan & Zheng, 2021; Nita et al., 2022; Szczakowska et al., 2023). Moreover, there is also a concern regarding an individual's privacy. Deep learning models typically require large datasets to prevent overfitting, which is a common issue when training models on small or homogeneous datasets (Chlap et al., 2021).

In the domain of handwriting analysis, the recognition of emotions through handwriting analysis has received relatively less attention, despite its potential as a non-intrusive and cost-effective approach (Alai & Afreen, 2023). These methods aim to assess an individual's personality characteristics by studying their handwriting patterns, with the underlying principle that a person's handwriting can reveal insights into their subconscious mind and behavioral tendencies. The current landscape of emotional state recognition underscores the need for effective and accessible methods to identify and address mental health conditions like depression, anxiety, and stress. These conditions significantly impact individuals' quality of life and contribute to substantial healthcare costs globally (World Health Organization, 2017). In the Philippines, nearly 1 in 10 young adults (8.9%) suffer from moderate to severe depressive symptoms, with those experiencing these symptoms being at greater risk of contemplating suicide (Puyat et al., 2021). Early detection and intervention can mitigate the adverse effects of these conditions, and identifying potential indicators through non-invasive means could facilitate timely support and treatment (Esposito et al., 2020). However, there is

insufficient public data to develop accurate models for emotion recognition using handwriting and drawing samples.

Collecting and labeling large amounts of data in this domain is time-consuming and expensive, leading to a lack of data and making it difficult to build reliable models for emotion identification from handwriting and drawing samples (Szczakowska et al., 2023; Khan et al., 2024). To address this challenge, data augmentation techniques have shown potential by generating synthetic datasets that cover unexplored input spaces while maintaining correct labels, thereby increasing the size and diversity of training datasets (Wen et al., 2021b). Data augmentation involves generating synthetic data to increase the size and diversity of a dataset, which helps improve the generalization and performance of machine learning models (Hou et al., 2022).

In collecting online handwriting data, several characteristics are recorded, including multiple variables such as the pen tip's X and Y-axis positions, pen status, pressure, azimuth angle, altitude angle, and timestamp. This data is typically gathered using devices like tablets and styluses (Khan et al., 2024). In psychological applications, such as Parkinson's disease detection and emotional state recognition systems, the data is derived from drawings of shapes like clocks, pentagons, circles, and houses, as well as from writing words and sentences (Likforman-Sulem, 2017). These activities are used to gather information on cognitive, emotional, and developmental status.

Most studies on handwriting have focused primarily on movements made while the pen is on the writing surface. However, some studies emphasize the significance of in-air movements, which can only be tracked when the pen tip is within about 1 cm of the surface. Beyond this range, the data is lost (Faundez-Zanuy et al., 2020). Missing data can reduce efficiency, complicate analysis, and introduce biases between complete and incomplete datasets (Barnard & Meng, 1999; Farhangfar et al., 2007). Two common methods to address missing data are deletion and imputation (Cheema, 2014). Deletion

involves removing partially observed samples or features, which can create dataset gaps and lead to incorrect parameter estimations (McKnight et al., 2007; Graham, 2009). Imputation, on the other hand, estimates and fills in missing values, preserving the dataset's integrity and allowing for a more accurate and complete analysis (Rubin, 1976). While deletion is straightforward, it can result in significant information loss when missing data is abundant (Guo, 2019). Imputation leverages all available information to fill in missing data, making it a more practical and effective approach.

In previous studies focusing on handwriting data for emotional state recognition, only a few data augmentation techniques have been utilized, primarily relying on geometric transformations. However, these methods have drawbacks, as they require expert knowledge to maintain correct labels (Abayomi-Alli, 2021). For instance, Flores et al. (2021) introduced Gaussian white noise as an augmentation technique to generate additional reliable observations, addressing the imbalance issue in the EMOTHAW dataset. Similarly, Nolazco-Flores et al. (2021; 2022) employed Gaussian random noise to ensure that the data had an equal number of observations, effectively mitigating the imbalance problem. Additionally, existing data augmentation techniques for time series data have primarily focused on univariate datasets, overlooking the complexities and nuances of multivariate time series data, such as handwriting (Yang & Desell, 2022). Various studies have explored data augmentation in handwriting, but imputation remains underexplored despite the presence of missing data (Flores et al., 2021; Najda & Saedd, 2022; Otero et al., 2022).

Additionally, Earlier statistical imputation methods like ARIMA, ARFIMA, and SARIMA, along with machine learning techniques such as regression, K-nearest neighbor (KNN), matrix factorization, and MICE, have been used for imputing missing values in multivariate time series.

However, these traditional imputation techniques often fail to perform adequately for multivariate data, as they do not effectively utilize the inherent correlations across features (Pourshahrokhi et al., 2021). Deep generative models like Variational Autoencoders (VAEs) and Generative Adversarial Networks (GANs) have shown superior performance for data imputation by effectively modeling complex dynamics and learning the underlying data distribution, leading to more accurate and reliable imputation of multivariate time series data (Wang et al., 2024).

VAEs excel in capturing and generating the underlying distribution of real data, making them particularly suitable for generating synthetic tabular datasets (Bang et al., 2024). GANs have also been employed to tackle the imputation challenge, with models like MTS-GAN (Guo et al., 2019) and E2GAN (Luo et al., 2019) utilizing the adversarial training framework to generate realistic imputations for missing values (Wang et al., 2024). However, GANs are notoriously difficult to train, susceptible to mode collapse, and lack evaluation metrics (Iglesias et al., 2023). They also face limitations in modeling the complex distributions of multivariate time series data (Guo et al., 2019; Li et al., 2022). VAEs may produce low-quality data as they optimize for reconstruction loss (Ham et al., 2020).

To overcome these limitations, combining the strengths of VAEs and GANs into a hybrid model called VAE-GAN has been proposed over the years (Ruan et al., 2023). VAE-GAN utilizes the latent variable model of VAE to generate data and uses the discriminator of GAN to evaluate the authenticity of the generated samples (Iglesias et al., 2023). This combination allows the model to enhance its generative capabilities by producing more high-quality and diverse samples of time series datasets (Hu et al., 2023). However, scenarios where missing values are drawn from a different distribution than the training data pose a challenge for VAE-GAN. To address this, researchers have introduced shift-correction (SC) variants, such as SC-β-VAE (Li et al., 2021) and SC-VAE

(Qiu et al., 2020), which modify the assumption of the training data distribution to follow a shifted Gaussian. Additionally, the β-VAE variant, a generalization of VAE that balances reconstruction loss and regularization loss through a hyperparameter β, has been explored to improve imputation performance (Qiu et al., 2020).

The proposed solution of combining VAE and GAN with shift correction and beta regularization (SC-β-VAE-GAN) aims to leverage the strengths of these individual models while mitigating their drawbacks. By integrating the generative capabilities of VAEs (Bang et al., 2024), the adversarial training framework of GANs (Wang et al., 2024), and the shift correction and regularization techniques, the SC-β-VAE-GAN model has the potential to provide a robust and effective solution for data augmentation and imputation. To the best of the authors' knowledge, this is the first approach to utilize a VAE-GAN hybrid for the purpose of data imputation. This approach is particularly valuable in domains where data collection is challenging or time-consuming, such as healthcare, physics, and psychology, as it maximizes the utility of available data while ensuring high-quality synthetic samples and accurate imputation of missing values, even in scenarios where the missing data exhibits specific patterns or is drawn from a different distribution than the training data. Furthermore, the SC-β-VAE-GAN model can potentially be applied to a wide range of applications beyond handwriting recognition, extending its usefulness to other domains or scenarios involving multivariate time series data.

Theoretical Framework

VAE-GAN (Variational Autoencoder Generative Adversarial Network). This is a model that combines the strengths of Variational Autoencoders (VAEs), which learn an efficient latent representation, and Generative Adversarial Networks (GANs), known for generating realistic samples (Mishra, 2024).

Razghandi et al.'s (2023) VAE-GAN model architecture, depicted in Figure 1, includes an encoder that encodes the input sequence (x1, x2, ...) into a Gaussian distribution over the latent space, represented by mean and variance vectors. A supervisor trains the encoder to closely approximate the next time step in the latent space based on the input sequence. Additionally, a generator reconstructs the sequence from the latent space, attempting to produce a sequence that fools the discriminator into considering it real. The discriminator distinguishes between the real input sequences and the generated (fake) sequences from the generator. This model is particularly useful for tasks like sequence generation, where the goal is to generate realistic sequences that match the training data distribution. This makes the VAE-GAN model important for this study.

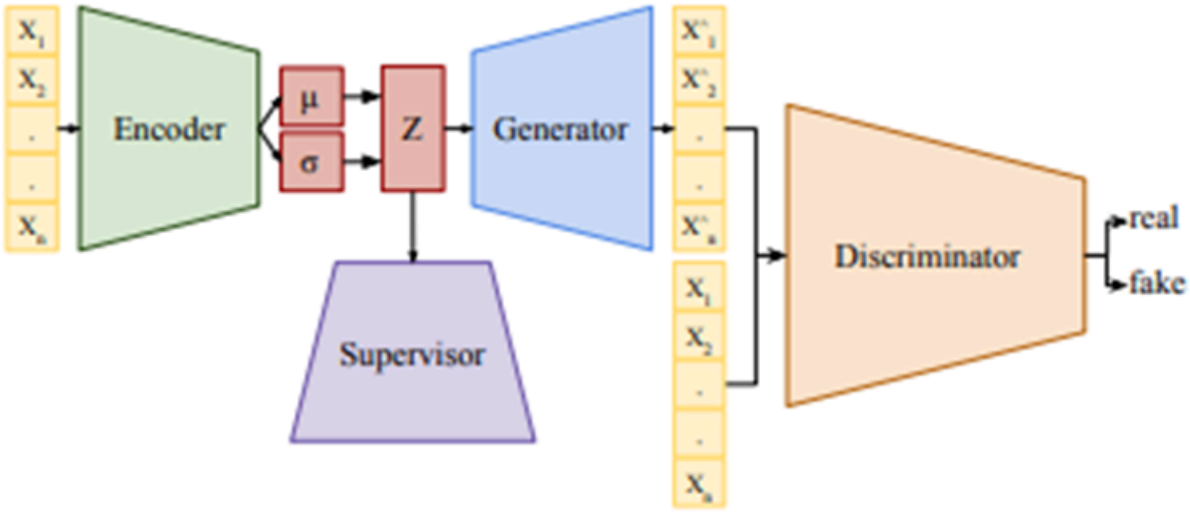

Figure 1. VAE-GAN Model Architecture (Razghandi et al., 2023)

VAE based on Shift Correction. According to Li et al. (2021), this model is a modified standard VAE model designed to fill in missing values in data samples. This correction aims to counteract the deviation caused by missing values. It is applied in the Gaussian latent distribution, where a shift hyperparameter λ is manually set to center the latent distribution, thus correcting the possible bias produced by missing values. In their

model, as shown in Figure 2, Li illustrates how the VAE architecture is used to impute missing values.

The architecture includes an inferential network acting as the encoder part of the VAE, which takes input data (A1, A2, ..., An) and encodes it into a latent space representation, parameterized by mean (μ) and variance (σ2) vectors. The latent space contains the learned compressed representation of the input data, where each data point is encoded as a distribution in this space, defined by the μ and σ2 vectors from the inferential network. A generator acts as the decoder part of the VAE, taking samples from the latent space and generating/reconstructing the output data (B1, B2, ..., Bn). The model incorporates a shift correction mechanism, represented by the term (1 + Σi |xi - xi|) in the diagram. This term penalizes temporal shifts between the generated data and the input data, ensuring better alignment in the time dimension. This shift correction-based model is designed to learn a disentangled latent representation of the input data while ensuring good reconstruction quality. The shift correction mechanism specifically addresses the issue of temporal misalignment in the generated data, making it suitable for applications involving time series data or sequential data tasks, as in this study.

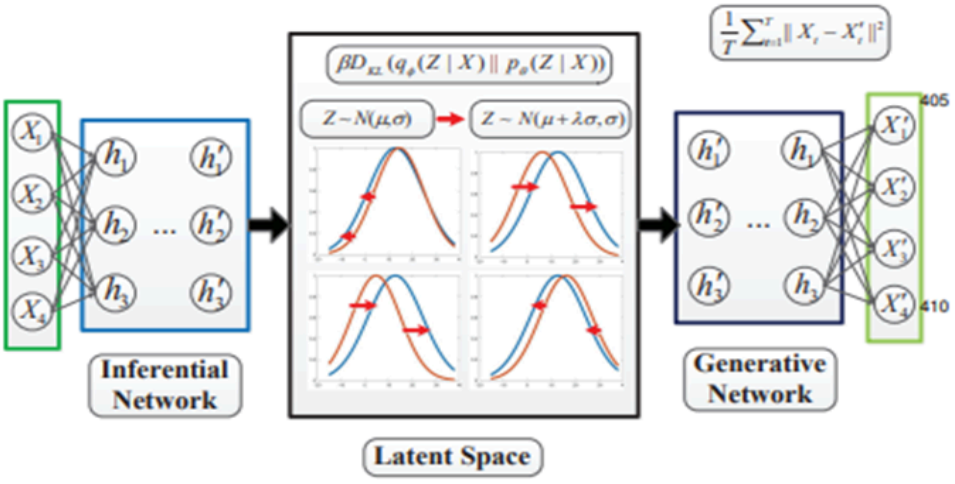

Figure 2. VAE based on Shift Correction Model Architecture (Li et al., 2021)

Conceptual Framework

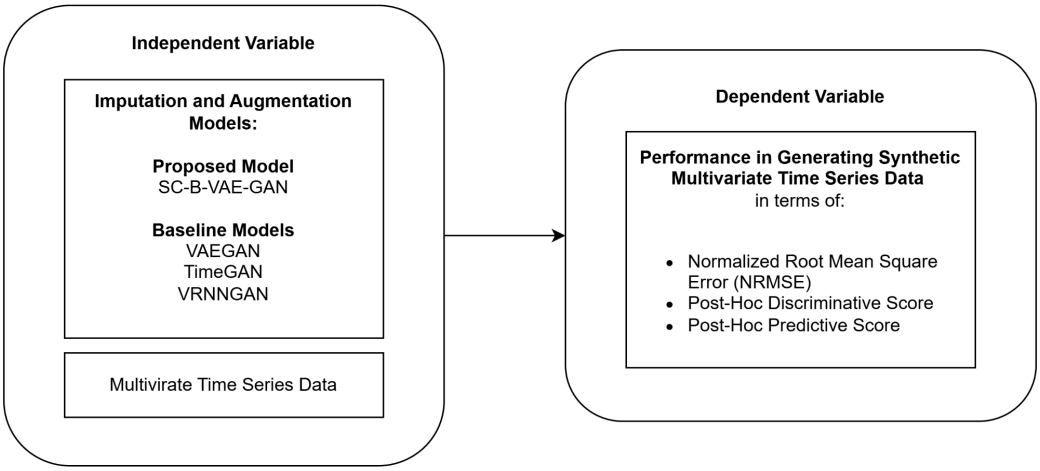

Figure 3. Conceptual Framework of the Study

Figure 3 illustrates the conceptual framework of the study, outlining the core components and objective of the study. The primary focus is to evaluate the proposed model and compare its performance on baseline augmentation models for generating synthetic multivariate time series data.

The independent variable comprises the proposed SC-β-VAE-GAN (Shift Correction Beta Variational Autoencoder Generative Adversarial Network) model, which is a modified approach developed by the researchers. Also, baseline models, namely VAE-GAN, TimeGAN and VRNNGAN, are included for comparative analysis of how the proposed and modified model performed based on the performance of similar models. These techniques will be trained and applied to the multivariate time series data which serves as the input.

To check how the models performed, dependent variables are presented. Dependent variables include the performance indicators used to assess how accurately these models perform time series synthetic data generation. Specifically, three metrics are employed: Normalized Root Mean Square Error (NRMSE), Post-Hoc Discriminative

Score, and Post-Hoc Predictive Score. These metrics quantify the similarity between the generated synthetic data and the real data, evaluating both the statistical properties and the ability to preserve temporal dependencies and patterns.

By systematically evaluating the proposed SC-β-VAE-GAN model and the baseline models using these performance metrics, the researchers aim to determine if the proposed model will be an effective approach for imputing and augmenting multivariate time series data.

Statement of the Problem

Analyzing online handwriting data has proven useful in various fields. However, challenges such as limited data and missing data have hindered the quality of previous studies. To address these issues, the study aims to develop SC-β-VAE-GAN, a shift correction VAE-GAN model, to generate synthetic data for imputation and augmentation. The study aims to address the following questions:

1. What is the performance of the SC-β-VAE-GAN in generating synthetic data, based on the following metrics:
    1.1. Normalized Root Mean Square Error (NRMSE)
    1.2. Post-Hoc Discriminative Score
    1.3. Post-Hoc Predictive Score
2. What is the performance of VAE-GAN, TimeGAN, and VRNNGAN in generating synthetic data, based on the following metrics:
    2.1. Normalized Root Mean Square Error (NRMSE)
    2.2. Post-Hoc Discriminative Score
    2.3. Post-Hoc Predictive Score

3. Is there a significant difference between SC-β-VAE-GAN and other modes, specifically: A. VAE-GAN B. TimeGAN C. VRNNGAN; in terms of generating synthetic data?

Hypotheses

H_0 - There is no significant difference between the performance (NRMSE, Post-Hoc Discriminative Score, Post-Hoc Predictive Score) of SC-β-VAE-GAN and VAE-GAN in terms of generating synthetic data.

H_0 - There is no significant difference between the performance (NRMSE, Post-Hoc Discriminative Score, Post-Hoc Predictive Score) of SC-β-VAE-GAN and TimeGAN in terms of generating synthetic data.

H_0 - There is no significant difference between the performance (NRMSE, Post-Hoc Discriminative Score, Post-Hoc Predictive Score) of SC-β-VAE-GAN and VRNNGAN in terms of generating synthetic data.

Scope and Limitations of the Study

This study focuses on developing a system capable of generating synthetic data for imputation and augmentation. A Generative Adversarial Network (GAN) framework will be incorporated where a Variational Autoencoder (VAE) with shift correction and hyperparameter β will be the generator, and the Long Short-Term Memory (LSTM) network will be the discriminator. The experimentation will use multivariate time series dataset, specifically online handwriting data to generate synthetic data. Additionally, a GPS Time Series data will be used to validate the model's applicability to other time series dataset. Furthermore, a comparison between the proposed system, SC-β-VAE-GAN, and other systems such as VAE-GAN, TimeGAN and VRNNGAN will be conducted.

The study will not include offline handwriting datasets or images containing handwriting data, as it involves different types of data representation. Unlike offline handwriting, which captures static images of written text, online handwriting mainly records dynamic information such as pen position, pressure, and timing as the writing process is happening. Aside from that, classification of these data will not be part of the study as our main goal is to generate synthetic data.

Significance of the Study

The proposed study on the development of a Shift Correction β-VAE-GAN Model for Imputation and Augmentation of Handwriting Multivariate Time Series Data will address challenges associated with limited data and missing data. It can offer valuable insights and applications across different domains.

AI and Machine Learning Professionals - The introduction of shift correction and β adjustments into the VAE-GAN framework has the potential to lead to significant advancements in data augmentation and imputation. These improvements could address critical issues such as enhancing data variability and handling missing values, both essential for effective model training. This advancement could greatly benefit AI and machine learning professionals by providing them with potentially more effective tools for data augmentation and imputation of multivariate time series data.

Graphologists - By improving methods for augmenting and imputing handwriting time series data, these models could provide higher quality data, potentially leading to more accurate and reliable analysis in graphology. This could deepen insights into personality traits, cognitive states, and emotional conditions derived from handwriting, ultimately enhancing the validity and reliability of their findings.

Future Researchers - The advancements proposed in this study, particularly the integration of shift correction and Beta into the VAE-GAN model, could be used as reference for future research. Researchers might be able to build upon these improvements to further enhance data handling techniques, explore new applications, and continue advancing the fields of machine learning and data science.

Definition of Terms

1. **Data Augmentation** - A process that involves modifying cases in the training set to increase data diversity without collecting new data, thereby enhancing model generalization.
2. **Data Imputation** - A process that fills in missing values in a dataset using various techniques trained on observed data, restoring complete datasets for analysis or modeling.
3. **Missing Data** - Data that are absent or unavailable in a dataset.
4. **Synthetic Data** - Artificially generated data that imitates the characteristics of real-world data, used for research, testing, and training models when real data is unavailable or sensitive.
5. **Graphology** - The scientific method of assessing personality characteristics by studying handwriting patterns.
6. **Online Handwriting** - Captures the real-time movement of a pen or stylus on a digital surface, recording data such as position, azimuth, altitude, pen status, and pressure for analysis and recognition.
7. **Time Series Data** - A sequence of data points collected at consistent time intervals, used to analyze trends and patterns over time.
8. **Multivariate Time Series Data** - A type of time series data that consists of multiple time-ordered and time-dependent variables.

9. **Variational Autoencoder (VAE)** - A neural network model for unsupervised learning that encodes and decodes data into a latent space, enabling the generation of new data. It is used as the generator component in the VAE-GAN model.
10. **Shift Correction** - An adjustment in VAEs that changes the mean of the latent vector to correct distribution errors caused by missing data.
11. **Generative Adversarial Network (GAN)** - A neural network model with a generator and discriminator trained together to produce realistic data samples. It enhances VAE by improving data realism through adversarial training in the VAE-GAN model.
12. **Long Short-Term Memory (LSTM)** - A recurrent neural network for modeling long sequences of data. It acts as the discriminator in the VAE-GAN model.
13. **Normalized Root Mean Square Error (NRMSE) -** A metric that evaluates the feature error or difference between the original data and the synthetic data, providing a normalized measure of the overall discrepancy between the two datasets.
14. **Post-Hoc Discriminative Score -** A metric that assesses how realistic and similar the generated data is compared to real-world data, indicating the ability of the synthetic data to mimic the statistical properties of the original data.
15. **Post-Hoc Predictive Score -** A metric that evaluates the predictability and the preservation of patterns in the synthetic data, ensuring that it retains the underlying structures necessary for predictive modeling and analysis.

Chapter 2

REVIEW OF RELATED LITERATURE AND STUDIES

The section reviews the literature and studies that support the use of the proposed SC-β-VAE-GAN model for imputation and augmentation of handwriting multivariate time series data. The literature review covers eight recurring themes: handwriting data, time series data, data augmentation, data imputation, the combination of data augmentation and imputation, generative adversarial networks (GANs), variational autoencoders (VAEs), and VAE-GANs. These themes offer a structured approach to understanding the various methods, gaps, challenges, and limitations within the research topic.

I. Handwriting Data

Handwriting is a multi-sensory activity and skill that plays a crucial role in life (Alaei & Alaei, 2023). Each individual possesses a unique handwriting style that could reflect one's personality and psychology. The characteristics drawn from handwritten data motivated researchers to explore this area for over a decade. And it has been used in various applications including user authentication, assessment of neurodegenerative disorders, and classification of handedness, gender, and age groups (Hasan et al., 2024). This can be beneficial for professionals and experts in assessing or addressing specific issues in these fields.

A handwriting system can be categorized into two, online and offline. The latter are typically represented by digitized images extracted from documents, typically from a pen and paper sample containing handwritten data. Meanwhile, online handwriting data requires specialized hardware, including a digitalized tablet or pen to capture signatures directly (Taleb et al., 2020). Extracting features from the two handwriting samples can be categorized into two, micro and macro. The latter describes the overall pictorial

characteristics (size, slant, shape, and space between the words and characters), whereas micro features describe the attributes of individual characters/components, for example, the geometry or shape of the individual characters (Alaei & Alaei, 2023). Moreover, offline handwriting samples use image-processing techniques to extract features, while online handwriting samples use signal-processing methods (Velazquez-Flores, 2021). Extracting these characteristics is important as it could help intelligent systems to accurately predict or classify an individual.

1. **Offline Handwriting Data**

Recognition of handwriting and drawing images have been widely researched over the past decade. Offline handwriting can be described as the process of converting handwritten or drawn images to its digital form. It has a variety of applications ranging from digital character conversion to signboard translation and scene image analysis (Singh et al., 2023). Automatic classification such as of gender and age has been a subject for researchers, and it has been proven that several handwriting characteristics relate to a gender. Male usually are more angular, disorderly, and slanted than females. And some studies have also shown that age can affect the writing performance of an individual.

In a study by Rabaev et al. (2022), they develop a system that can automatically detect gender and age that can be beneficial in some fields such as forensics and historical document analysis. They proposed B-ResNet where they used the B-CNN Architecture with ResNet instead of VGG blocks. Furthermore, they used a combination of three offline handwriting datasets namely KHATT which composes of 1000 handwritten Arabic images made by high school and university students, QUWI dataset that includes handwriting samples written in

English and Arabic, as well as HHD dataset which contains Hebrew handwritten images for gender detection.

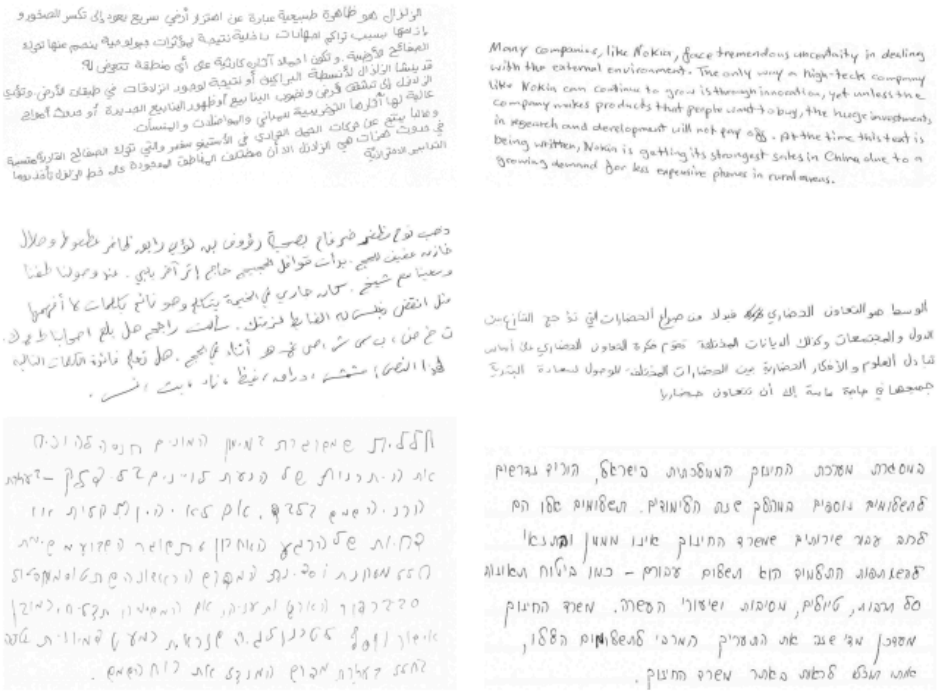

Figure 4. Handwritten images from the KHATT, QUWI, and HHD databases (Rabaev et al., 2022)

These datasets were represented by two parallel ResNet models and concatenated to the bilinear vectors that are fed to the classification layer. The results of their experimentation showed that the proposed model has a higher classification accuracy for gender detection compared to other models except for HHD dataset, and the combination of English and Arabic handwriting images from QUWI dataset. Additionally, the proposed model also yielded higher accuracy for age classification for three and four age classes.

The study of Ozyurt et al. (2024) proposed a novel approach for handwriting signature verification. First, they collected a dataset containing 12,600 handwriting signature images from 420 individuals each containing 30

distinct signatures. The features from these images were extracted using MobileNetV2, and used three different feature selection techniques namely neighborhood component analysis (NCA), Chi2, and mutual_info (MI). Using these three techniques, they were able to select 200, 300, 400, and 500 relevant features from the images. These were fed to different machine learning models such as SVM, KNN, DT, Linear Discriminant Analysis, and Naive Bayes. The results of their experimentation showed that classification without using any feature selection technique yielded a 91.3% accuracy while NCA with 300 features had a high accuracy of 97.7%.

While there is already a lot of advancement in this area, it is still a field that researchers are focusing on because of its demand applicability in different domains including handwritten manuscript recognition, bank form recognition and historical document processing (Wang et al., 2021). Moreover, offline handwriting recognition itself is complicated as there are a lot of variations in writing styles, character types, and complicated structure of texts (Wang et al., 2021). Unlike online handwriting, tasks for offline handwriting recognition can be divided to smaller ones like paragraph detection, text-line segmentation, word/character segmentation, image normalization (Wang et al., 2021).

2. **Online Handwriting Data**

Online handwriting data captures multiple variables such as the pen tip's X and Y-axis positions, pen status, pressure, azimuth angle, altitude angle, and timestamp (Khan et al., 2024). Researchers use online handwriting analysis to determine and understand various traits of individuals, including personality, neurodegenerative diseases, emotional states, gender, age, and nationality. This data is gathered using devices like tablets and styluses.

The rich metrics provided by online handwriting analysis make it an effective tool for the early detection of health conditions and diseases. It offers a non-invasive diagnostic method that can be conveniently administered by non-technical personnel in the patient's environment without disrupting daily routines. Additionally, it provides a cost-effective solution, requiring minimal infrastructure or medical equipment, and delivers information swiftly and affordably (Otero et al., 2022).

Rahman and Halim (2022) explored the use of tablet devices to non-invasively determine emotional states through handwriting and drawing acquired from the publicly available EMOTHAW (EMOTional State Recognition from HAndwriting and DraWing) database. They specifically used temporal, spectral, and Mel Frequency Cepstral Coefficients (MFCC) for feature extraction and employed BiLSTM networks for classifying these features. Additionally, spatial features such as velocities in the x- and y-directions were examined. Utilizing multiple public benchmark datasets, the research identifies specific activities and features correlating with emotional states like depression, anxiety, and stress, achieving a significant improvement in classification accuracy by 5.32% to 8.9% overing the number of data for training deep learning models like BiLSTM. The researchers recommended deploying data augmentation techniques such as the Piecewise Cubic Hermite Interpolating Polynomial (PCHIP) and spline-based interpolation techniques. These methods generate synthetic data samples to address issues with small datasets that suffer from class imbalance and susceptibility to overfitting.

Khan et al. (2024) also explored identifying negative emotions such as depression, anxiety, and stress through online handwriting and drawing data. A deep learning network, specifically an attention-based transformer, was used to

analyze handwriting samples to determine emotional sr baseline methods. The proposed method exhibited promising results of 92.64% on the EMOTHAW dataset. However, they encountered challenges in developing the model due to the limited diversity in handwriting and drawing styles within the training data, impacting the model's reliability and generalizability for emotion identification.

Most online handwriting research focuses on pen-on-paper movements, but in-air movements are also significant. Greco et al. (2023) found that depressed patients spent more time with the pen in-air (Up) and on paper (Down) and took longer to complete tasks compared to healthy participants. Specific tasks like writing words, drawing clocks, and writing sentences revealed longer in-air and overall times for depressed individuals, who also had more unrecognized and fewer total pen strokes. Kunhoth et al. (2023) demonstrated that including in-air features significantly improved machine learning classifiers for diagnosing dysgraphia. Classifiers combining on-surface and in-air features outperformed those using only on-surface features, with the AdaBoost classifier achieving 80.8% accuracy compared to 72.5%. Gargot et al. (2020) found that in-air movements correlate with handwriting quality and speed in typically developing children, with less in-air movement linked to better handwriting. Children with severe dysgraphia showed abnormalities in kinematics, pressure, and tilt. These studies highlight the importance of in-air features in enhancing the accuracy and reliability of handwriting analysis.

However, a limitation of this approach is that tracking pen movements when the tip is in the air is restricted to a range of about 1 cm from the surface, resulting in data loss beyond this range (Faundez-Zanuy et al., 2020). Such data loss can significantly reduce the dataset's size and eliminate valuable information

crucial for analysis, potentially biasing results by inadequately representing the original data's scope and nature (Zhu et al., 2024).

II. Time Series Data

Time series data are usually collected from various real-world systems (Chawla et al., 2019) and have been a key area of academic research in different applications (Lim & Zohren, 2021). This area of research is growing over time as changes in data for various processes are recorded and needed for numerous global processes, especially to solve problems related to big data (Torres et al., 2021) and to capture the dynamic changes and patterns that occur over time (Lim & Zohren, 2021). These data are collected from various sources, including sensors, financial markets, and social media platforms, and are used to analyze and forecast future trends and behaviors (Buaton et al., 2019). The importance and quality of time series data lies in their ability to provide valuable insights into complex systems, enabling researchers and practitioners to identify patterns, make predictions, and inform decision-making processes (Lim & Zohren, 2021).

Time series data usually have values for a given entity I at time T. This entity represents the temporal information needed for data analysis, capturing how a specific attribute of interest changes over time. The variable T denotes the specific times at which observations of the entity are recorded, providing a sequential snapshot that allows for trend analysis, forecasting, and other time-dependent evaluations. Understanding the temporal dynamics of an entity through time series data is crucial for making informed decisions and predictions in various fields such as finance, healthcare, and environmental studies (Lim & Zohren, 2021). The analysis and processing of time series data have become increasingly crucial in today's data-driven world, particularly in the context of big data and the Internet of Things (IoT). As the volume and complexity of

time series data continue to grow, new methods and techniques are being developed to effectively extract insights and make accurate predictions (Choi et al., 2021).

Within time series data, univariate and multivariate datasets offer distinct perspectives. Univariate data involve a single feature variable, with measurements focusing on one aspect at a time. This type of data is useful for understanding the behavior and trends of a single attribute over time. In contrast, multivariate data involve multiple feature variables measured simultaneously or at different frequencies. This type of data provides a comprehensive view by capturing the interplay between various attributes over time, allowing for a more holistic analysis and richer insights (Weerakody et al., 2021).

1. Multivariate Time Series Data

Multivariate time series data is a type of data that contains different types of behaviors in different working periods of the system. These multivariate periodic recorded data contain multiple variables compared to univariate which only has one variable (Sürmeli & Tümer, 2019). Its data has gained importance in various domains such as medicine, finance, multimedia, and nearly every field that operates with temporal datasets. This type of data is characterized not only by individual attributes but also by their interactions. The consideration of multiple attributes can make processes like prediction, pattern finding, and augmentation more complex and tedious (Baydogan & Runger, 2014).

The complexity of multivariate time series (MTS) data requires a more rigorous and complex approach for implementing unsupervised learning and clustering analysis, given that multiple characteristics are present in each log. In addition, as MTS is relatively new compared to univariate time series (UTS), some time-series-related studies have focused only on single-variable time series

due to the absence of high-dimensional features (Li & Du, 2021). MTS, on the other hand, is not only multi-dimensional and high-dimensional but also typically has an extended time dimension, numerous attribute variables, and large data volumes. This poses a challenge for data analysis, machine learning, data recognition, and other related domains (Baldán & Benítez, 2021).

2. Handwriting as Multivariate Time Series Data

Handwriting analysis and recognition are fields that extensively utilize multivariate time series data.This type of data involves multiple variables recorded over time, capturing the dynamic and complex nature of handwriting (Morrill et al., 2020), as shown in Figure 5. Each variable, such as pen pressure, stroke direction, and velocity, provides crucial insights into the mechanics and characteristics of handwriting, facilitating a deeper understanding of how handwriting is produced and its distinct attributes (Lee et al., 2022).

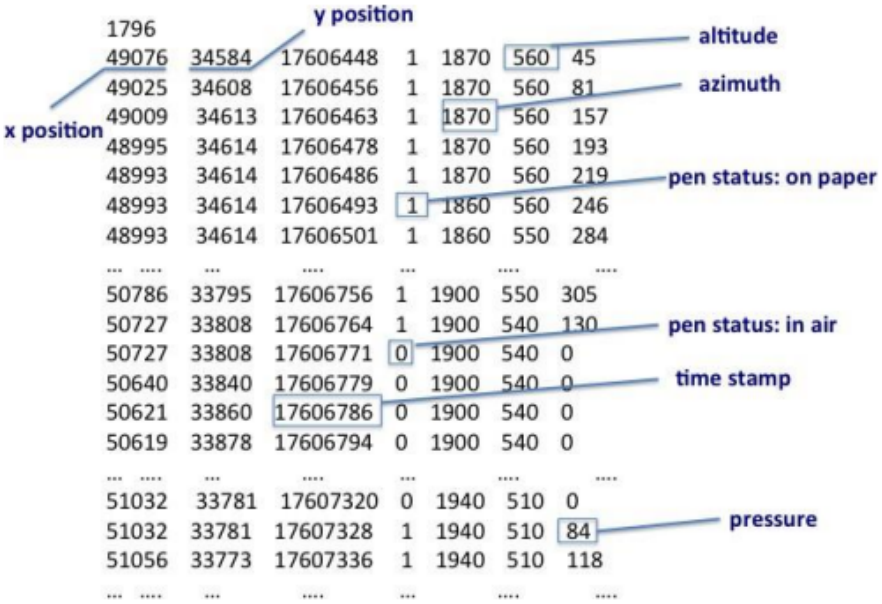

Figure 5. Extracted online handwriting variables (Likforman-Sulem, 2017)

Handwriting recognition is a prominent application of multivariate time series data, where the temporal sequences of different handwriting features are analyzed to accurately interpret written text. The intricacies of these multivariate characteristics pose challenges for traditional learning algorithms, necessitating advanced techniques for effective analysis and recognition (Morrill et al., 2020) Study by Azimi et al, uses online handwriting data in experimenting the different machine learning and deep learning models for handwriting recognition. Researchers found that since the sensor captures a lot of information pieces such as the time it takes to write, cadence and stylization making it more beneficial to understand more about the certain handwriting. (Azimi et al., 2023).

Their contributions include significant accuracy improvements in both Machine Learning (ML) and Deep Learning (DL) classifiers on the OnHW-chars dataset, with ML models showing a 11.3%-23.56% improvement and DL models achieving a 2.17%-4.34% increase over previous benchmarks. Additionally, the use of ensemble learning methods yielded further improvements of 3.08%-7.01%. The researchers also focused on providing explainability for their models, extending the LIME architecture to add interpretability to their multivariate time series data. They ensured the reproducibility and verifiability of their results by making their preprocessing code and models publicly available. Their study not only improved accuracy but also provided insights into why certain models are suitable for specific data types, contributing to the transparency and advancement of handwriting recognition research. Future work suggested includes optimizing ensemble methods and conducting deeper analyses on model explainability and feature importance (Azimi et al., 2023).

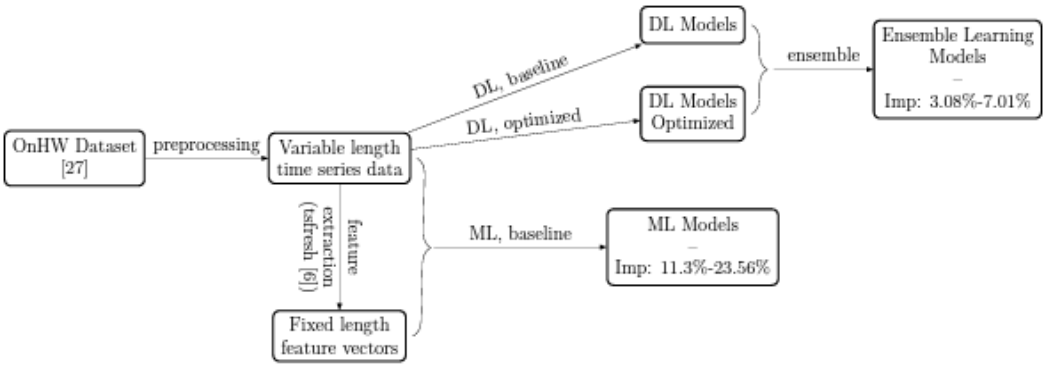

Figure 6. Workflow for training ML and DL models with ensemble method (Azimi et al., 2023)

A research by Lintonen & Raty tries to solve the problem of complexity in self-learning of the multivariate time series data by proposing a novel stopping criterion called Peak evaluation using perceptually important points. This criterion algorithmically adds the stopping criteria aiming to make the learning not undergo manually added hyperparameters on the system. It has been applied to different datasets such as heartbeat, wave gesture, basic motions, finger movements, handwriting, and many more. The result shows that it performs well for univariate and multivariate datasets, enhancing the accuracy of datasets, class balancing with a positive class dominance. Researchers, on the other hand, recommend that further study might be conducted following their research, specifically enhancing the data labeling process and examining the effects of multimodality of time series data (Lintonen & Raty, 2019).

III. Data Augmentation

The basic idea of data augmentation is to generate synthetic datasets that cover unexplored input spaces while maintaining correct labels. It is used to artificially increase the size and diversity of a training dataset by creating modified versions of the existing

data (Wen et al., 2021). This process involves applying a series of transformations, such as flipping, rotating, scaling, or adding noise, to the original data samples (Keskin, 2023). The resulting augmented dataset contains both the original samples and their transformed counterparts.

The primary purpose of data augmentation is to improve the performance and generalization capabilities of machine learning models, particularly in scenarios where the available training data is limited. In deep learning models, large amounts of data are generally required to prevent overfitting, which is a common concern when a model is trained on a small or homogeneous dataset (Chlap et al., 2021). The use of deep learning models has achieved remarkable success in many fields, including healthcare, climate science, industrial automation, and affective computing. However, these fields often suffer from limited data availability, as it is expensive and time-consuming to acquire well-annotated data (Pan & Zheng, 2021; Nita et al., 2022; Szczakowska et al., 2023), making data augmentation a practical solution. By exposing the model to a larger and more varied dataset, data augmentation aims to enhance the model's ability to learn robust representations and avoid overfitting.

1. Handwriting Data Augmentation

Several studies have been conducted in handwriting analysis by deploying different data augmentation techniques. In a study by Kamran et al. (2020), they proposed a novel approach by using deep transfer learning-based algorithms and different data augmentation techniques to create a robust model that can detect early symptoms of Parkinson’s Disease (PD). Different PD datasets such as HandPD, NewHandPD, and Parkinson's Drawing datasets were collected and used for the experimentation. During the latter, different combinations of datasets and data augmentation techniques such as flipping,

thresholding, rotation, illumination, and contrast were fed to the models. The results showed that pre-trained CNN with fine-tuned architecture models yielded high performance, most specifically when the data augmentation technique illumination was employed as it obtained a 99.22% classification accuracy. Furthermore, their experimentation results showed that their proposed model surpasses the state-of-the-art approach when diagnosing early Parkinson's Disease symptoms.

The study by Hamdi et al. (2021) proposed a novel approach by employing four different data augmentation strategies for online handwriting recognition of multi-language including Arabic and Latin script. They used four databases where 3 datasets namely ADAB, ALTEC-OnDB, and online_KHATT are for Arabic script, and UNIPEN is for Latin script. Their experimentation included the deployment of geometric, frequency, beta-elliptic, and hybrid data augmentation strategies and end-to-end CNN architectures were utilized to test the performance of their proposed method. The results of their experimentation yielded an improvement by reducing the character error rate (CER) and word error rate (WER) significantly.

Another research by Najda and Saedd (2022) implemented augmentation methods to expand the input data of their system for online signature verification. Drawing from current advancements in the field, they selected five augmentation techniques to enhance the dataset. Each method was applied with varying repetition rates for every signature, ranging from ×0 to ×40 times. These augmentation methods include interpolation with modifications by the authors, noise addition to time series also with modifications, signal scaling, signal rotation, and warping time series. Najda and Saedd (2022) consider the common properties in handwritten data. The study used the database SVC 2004, which

contains properties such as X coordinate, Y coordinate, Pressure, Interval, Pen state, Azimuth angle, and Elevation Angle. These properties are where patterns are extracted from and enable the creation of new feature metrics such as signature duration, pen lead velocity and acceleration, coordinates of discrete points drawn from the signature line, or means and standard deviations of individual signal components.

In a study by Otero et al. (2022), a multivariate Empirical Mode Decomposition (mEMD) method was proposed to generate artificial handwritten data for diagnosing Essential Tremor (ET) using a Long Short-Term Memory (LSTM) model. Frequency decomposition was performed, and Intrinsic Mode Functions (IMFs) were generated from it. These IMFs of the subjects were then utilized to generate artificial samples for training the LSTM model (see Figure 7.a and figure 7.b below). The BIODARW dataset was employed, comprising a total of 51 samples, with 24 from the ET group and 27 from the control group. The study focused solely on X and Y coordinates, as these handwriting characteristics can be obtained from any digital tablet and provide sufficient information for diagnosing essential tremor. Experimental results indicated a 10% improvement compared to test cases without the generated data.

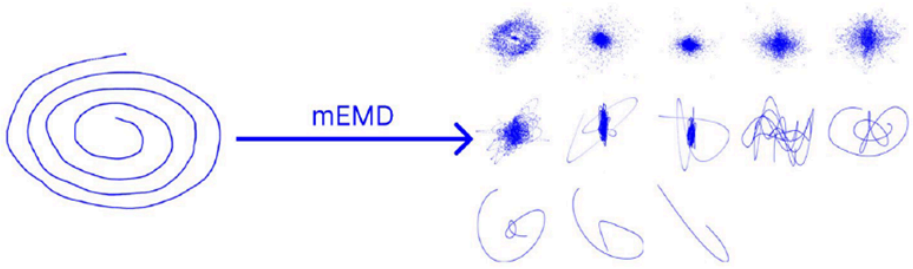

Figure 7.a. The process of generating IMFs from the original data using mEMD (Otero et al., 2022)

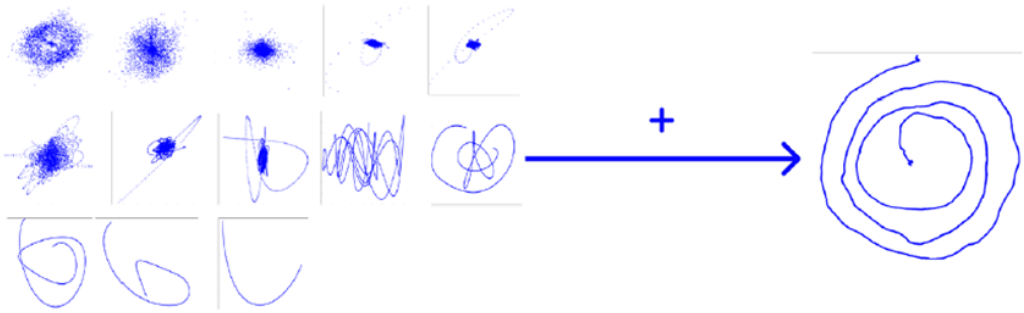

Figure 7.b. The process of generating IMFs from the original data using mEMD (Otero et al., 2022)

In previous studies focusing on handwriting data for emotional state recognition, only a few data augmentation techniques have been utilized, primarily relying on geometric transformations. However, these methods have drawbacks, as they require expert knowledge to maintain correct labels (Abayomi-Alli, 2021). For instance, Flores et al. (2021) introduced Gaussian white noise data as an augmentation technique to generate additional reliable observations, addressing the imbalance issue in the EMOTHAW dataset. Similarly, Nolazco-Flores et al. (2021; 2022) employed Gaussian random noise to ensure that the data had an equal number of observations, effectively mitigating the imbalance problem.

2. Time Series Data Augmentation

One area where deep learning has shown effectiveness but also faces limitations due to scarce data is time series analysis. Time series data poses unique challenges for data augmentation, as highlighted in Wen's (2021b) survey. This data, characterized by its inherent sequential nature and temporal dependencies, presents significant challenges for data augmentation. Efforts to

preserve underlying patterns while augmenting data are complicated, particularly as time series can be transformed into frequency and time-frequency domains for potentially more effective augmentation techniques. However, these methods become more complex with multivariate time series, where interactions across multiple variables over time must be carefully managed. Traditional augmentation methods from image and speech processing often fail to generate valid synthetic time time series data. Furthermore, the effectiveness of augmentation strategies is highly task-specific; techniques suitable for classification might not work well for tasks like anomaly detection or forecasting. The issue of class imbalance in time series classification further complicates the creation of a large, balanced set of synthetic data. Additionally, there is a notable deficiency in research on new methods for augmenting multivariate time series data, with many studies focusing solely on univariate data, which involves just a single input channel (Yang & Desell, 2022). The existing time series data augmentation methods across common tasks, including time series forecasting, anomaly detection, and classification, are outlined in Figure 8 (Wen et al., 2021b)

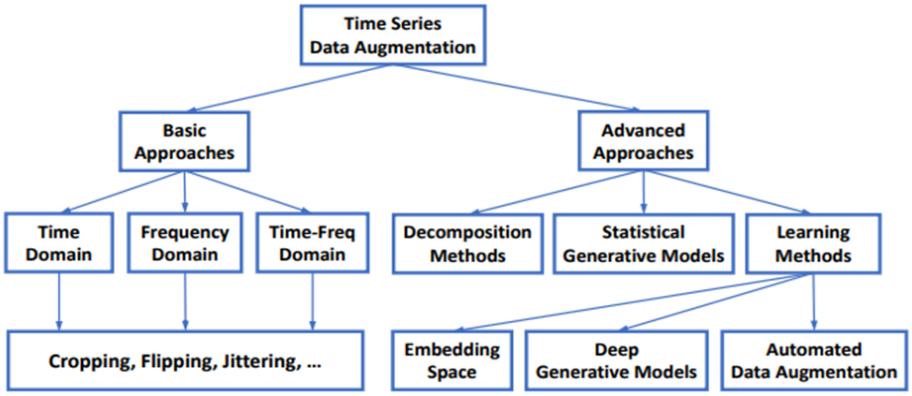

Figure 8. Taxonomy of time series data augmentation techniques (Wen et al., 2021b)

Basic data augmentation methods for time series can be categorized into two domains: time domain and frequency domain. In the time domain, methods such as window cropping, window warping (Gao et al., 2023), flipping (Wen & Angryk, 2024), and noise injection (Kim et al., 2023) are commonly used. These techniques involve manipulating the original time series by extracting slices, compressing or extending time ranges, flipping the sign of the series, and injecting noise patterns like Gaussian noise or spike-like trends. Additionally, label expansion in the time domain is utilized for anomaly detection tasks. In the frequency domain, perturbations in amplitude and phase spectra are applied to enhance time series data augmentation, offering improvements in anomaly detection tasks (Gao et al., 2020; Lee et al., 2019).

Advanced data augmentation methods for time series encompass decomposition-based, statistical generative, learning-based, and automated approaches. Decomposition-based methods, such as STL decomposition followed by recombination (Gao et al., 2020), utilize the components of time series like trend, seasonality, and residual signals to generate new synthetic data. Statistical generative models, like mixture autoregressive models (Kang et al., 2020), simulate time series data by describing conditional distributions based on historical data points. Learning-based methods leverage techniques like embedding space interpolation to generate diverse samples. Automated data augmentation employs reinforcement learning or evolutionary search strategies to automatically search for optimal augmentation policies, yielding significant improvements in classification accuracy for time series datasets (Cheung & Yeung, 2021).

Among advanced data augmentation methods, deep generative models have recently shown the ability to generate realistic high-dimensional data objects, such as images and sequences. DGMs developed for sequential data, like audio and text, can often be extended to model time series data. Generative adversarial networks (GANs) are particularly popular for generating synthetic samples and effectively increasing the training set, though generating effective time series data with GANs remains challenging (Wen et al., 2021b).

Combining basic time-domain methods, such as merging patterns and infusing noise, has been shown by Gao et al. (2024) to outperform using a single method and achieve the best performance in time series classification. While GANs are the primary deep generative model used for time series data augmentation, other models like Deep Autoregressive Networks (DARNs), Normalizing Flows (NFs), and Variational Autoencoders (VAEs) also hold great potential. Wen et al. (2021b) suggested exploring these less investigated models for time series data augmentation, presenting an exciting future opportunity that could lead to new and improved methodologies.

IV. Data Imputation

Missing data can lead to a loss of efficiency, complicate the analysis process, and introduce significant biases due to differences between complete and incomplete datasets (Barnard & Meng, 1999; Farhangfar et al., 2007). When dealing with the inevitable issue of missing data, which can arise from disruptions or malfunctions in data sampling and transmission, two common approaches are deletion and imputation (Cheema, 2014). Deletion involves removing samples or features that are only partially observed, which can leave gaps in the dataset and potentially lead to incorrect parameter estimations (McKnight et al., 2007; Graham, 2009). In contrast, data

imputation estimates and fills in missing values, allowing for more accurate and complete analysis. Imputation replaces missing values with estimated ones, preserving the dataset's integrity (Rubin, 1976). According to Guo (2019), although deletion methods are straightforward, they can result in the loss of valuable information when the proportion of missing data is high. In contrast, imputation methods aim to utilize all available information from the observations and fill in the missing data to create a complete dataset, making them a more practical and effective approach than simply discarding missing data.

1. Handwriting Data Imputation

Missing data, or missing values, occur when there is no data stored for certain variables or participants. Data can go missing due to incomplete data entry, equipment malfunctions, lost files, and many other reasons (Bhandari, 2021). In any dataset like handwriting, there are usually some missing data. This can be due to device errors or limitations. Any errors or limitations in the pen tablet device during data recording could result in missing or corrupted values for certain handwriting samples (Faundez-Zanuy et al., 2020). Another reason is incomplete writing samples. It's possible that for some keywords or iterations, a person may have failed to fully complete the writing, leading to missing values in the recorded data (Park et al., 2021).

Akash et al. (2020) proposes a user authentication system based on an individual's handwriting data collected from a pen tablet device. The dataset comprises handwriting samples from 24 individuals, each writing 10 defined keywords 5 times, resulting in 50 samples per person. Six key features are extracted from the handwriting data: writing time, pen pressure, x-axis angle, y-axis angle, horizontal angle, and vertical angle, which capture vital attributes of a person's handwriting style. The authors employed two methods for their

system. Method 1 involves basic feature extraction and classification using the Support Vector Machine (SVM) algorithm. Method 2 includes data pre-processing steps to balance the dataset format. Specifically, the Flatten Function is used to convert the 2D data to 1D form, and the Imputation Function fills in missing data values by averaging the same column. After pre-processing, four classification algorithms are used: SVM, Logistic Regression (LR), Linear Discriminant Analysis (LDA), and Random Forest (RF). The experiments show that Method 2 with pre-processing achieves better accuracy, with testing accuracy rates of 87% for SVM, 85% for LR, 76% for LDA, and 77% for RF. The imputation step plays a crucial role in balancing the dataset by filling in missing values with the column average, allowing the classifiers to work with a consistent and complete dataset format. However, even though this imputation is simple, it can introduce bias and ignore relationships with other variables (Huang, 2023).

Chang et al. (2020) present a method called "data incubation" to enhance handwriting recognition by strategically synthesizing missing data using a controllable generative model. Handwriting data is characterized by its content (the text written) and style (printed, cursive, neat, etc.), and it is challenging to collect sufficient real data that encompasses all content and style variations. To address this, they propose a controllable generative model trained on the available real data to synthesize new handwriting samples with underrepresented content (e.g., URLs, emails) and rare styles (e.g., cursive, slanted). The synthetic data is then combined with real data to train a more effective handwriting recognizer that can better generalize to unseen content and styles. Their framework analyzes and optimizes the synthetic data generation process by training recognizers on real data, synthetic data, and their combination, helping to identify issues like artifacts in synthetic data or missing style/content variations.

By carefully controlling the synthesis process, they achieve a 66% reduction in character error rate compared to training solely on real data, effectively imputing or filling in the missing data variations.

2. Time Series Data Imputation

Multivariate time series data often contains many missing values due to challenges in data collection. In areas like transportation (Zhang et al., 2021), healthcare (Kazijevs & Samad, 2023), and energy (Bülte et al., 2023), problems like sensor failures, unstable environments, and privacy issues can disrupt data collection. To address this, various imputation methods have been developed to fill in the gaps in multivariate time series data.

Earlier statistical imputation methods like ARIMA, ARFIMA, and SARIMA, along with machine learning techniques such as regression, K-nearest neighbor (KNN), matrix factorization, TIDER, and MICE, have been used for imputing missing values in multivariate time series. However, these methods often fail to capture complex temporal relationships and patterns and can suffer from bias due to case dropping or inappropriate data replacement (Wang et al., 2024). These traditional approaches are not ideal for high-dimensional data with fewer samples and perform inadequately for multivariate, highly dynamic data (Pourshahrokhi, 2021). Recently, deep learning methods, including Transformers, Variational AutoEncoders (VAEs), Generative Adversarial Networks (GANs), and diffusion models, have shown superior performance by effectively modeling complex dynamics and learning the true underlying data distribution, leading to more accurate and reliable imputation of multivariate time series data. In Figure 9, the overview of current deep multivariate time series imputation methods is presented (Wang et al., 2024).

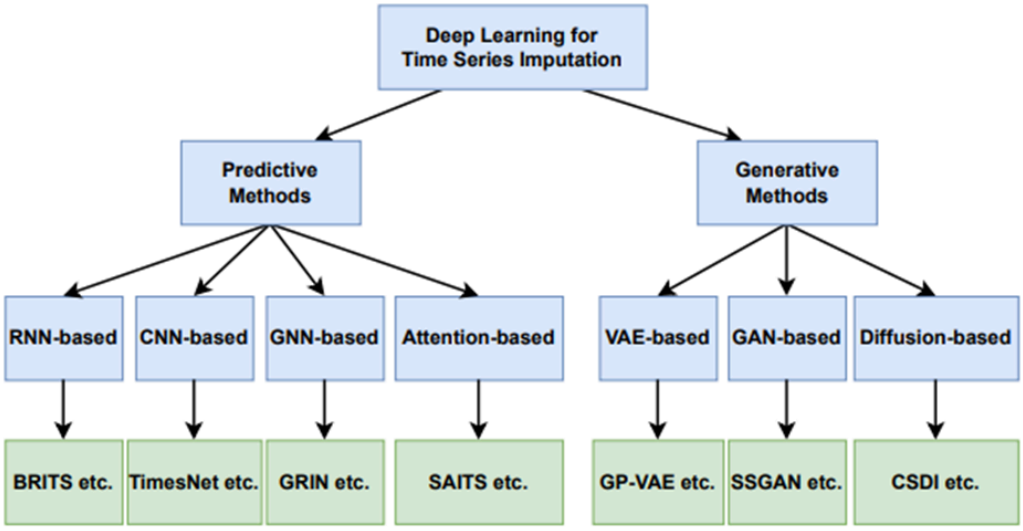

Figure 9.The taxonomy of deep learning methods for multivariate time series imputation (Wang et al., 2024)

Deep learning methods have revolutionized the imputation of missing values in multivariate time series data, offering superior performance by effectively modeling complex dynamics and learning the underlying data distribution. Among these, generative models using diffusion techniques have shown promising results. For instance, CSDI (Conditional Score-based Diffusion Models for Imputation) (Tashiro et al., 2021), SSSD (Score-based Stochastic Differential Equations) (Alcaraz and Strodthoff, 2023, TMLR), CSBI (Conditional Score-based Imputation) (Chen et al., 2023), MIDM (Missing Imputation using Diffusion Models) (Wang et al., 2023), PriSTI (Prior-based Score-based Time-series Imputation) (Liu et al., 2023), DA-TASWDM (Diffusion Augmented Time-series with Attention-based Score Weighing and Diffusion Modeling) (Xu et al., 2023), and SPD (Score-based Probabilistic Diffusion) (Bilos et al., 2023) utilize diffusion models combined with attention mechanisms to address missing

data under the MCAR (Missing Completely At Random) assumption. These models excel in capturing intricate temporal dependencies and spatial correlations, leading to highly accurate imputations.

In addition to diffusion-based approaches, generative models using Generative Adversarial Networks (GANs) have also been employed to tackle the imputation challenge. Unfortunately, GANs are not designed for sequential data, which is why research has been directed towards the development of hybrid models that use GANs as the underlying global concept (Richter et al., 2023). For example, models like MTS-GAN (Multivariate Time Series Generative Adversarial Network) (Guo et al., 2019), E2GAN (End-to-End Generative Adversarial Network) (Luo et al., 2019), NAOMI (Non-Autoregressive Multiresolution Imputation) (Liu et al., 2019), and SSGAN (Semi-Supervised Generative Adversarial Network) (Miao et al., 2021) utilize the adversarial training framework, typically combining GANs with RNNs (Recurrent Neural Networks), to generate realistic imputations for missing values under the MCAR (Missing Completely At Random) assumption. These GAN-based methods excel in generating high-quality synthetic data that closely resembles the original data distribution, making them highly effective for imputing missing values in multivariate time series.

Variational AutoEncoders (VAEs) have also been extensively explored for imputation tasks. Models such as GP-VAE (Gaussian Process Variational AutoEncoder) (Fortuin et al., 2019), V-RIN (Variational Recurrent Imputation Network) (Mulyadi et al., 2021), and supnotMIWAE (Supervised Non-Missingness Induced Variational AutoEncoder) (Kim et al., 2023) leverage the power of VAEs, often in combination with Convolutional Neural Networks

(CNNs) or Recurrent Neural Networks (RNNs), to handle missing data under various assumptions, including MCAR, MAR (Missing At Random), and MNAR (Missing Not At Random). These VAE-based models are adept at learning latent representations that can effectively capture the underlying structure of the data, resulting in robust and reliable imputation.

According to Rubin's theory (1976), missing data are typically grouped into three categories: Missing Completely At Random (MCAR), Missing At Random (MAR), and Missing Not At Random (MNAR). The assumptions of MCAR, MAR, and MNAR are crucial in imputation models because they define the nature of the missing data and influence the choice of imputation method. MCAR assumes that the missingness is completely random and independent of both observed and unobserved data, simplifying the imputation process. MAR assumes that the missingness is related to the observed data but not the unobserved data, allowing for more informed imputation based on available data. MNAR is the most challenging assumption, where the missingness is related to the unobserved data itself, requiring sophisticated models like VAEs that can learn from incomplete data and infer the missing values accurately. Understanding these assumptions helps in selecting appropriate models and techniques that can handle the specific nature of the missing data, ensuring more reliable and accurate imputations.

V. Data Augmentation and Data Imputation

In the realm of machine learning and data analysis, ensuring the quality and completeness of datasets is crucial for building robust models (Zhang et al., 2021). Two fundamental techniques that address these challenges are data augmentation and data imputation. Data augmentation involves generating synthetic data to increase the size

and diversity of a dataset, which helps improve the generalization and performance of machine learning models (Hou et al., 2022). Data imputation, on the other hand, focuses on estimating and filling in missing values within datasets to enable more accurate and comprehensive analysis (Huisman, 2000).

Combining data augmentation and data imputation is an innovative approach that takes advantage of the strengths of both techniques to enhance dataset quality. The rationale behind this combination lies in the complementary nature of these methods. Data augmentation enriches the dataset by adding variety, while data imputation fills the gaps caused by missing values. By integrating these techniques, one can simultaneously address data scarcity and missing values, leading to more reliable and effective machine learning models. This combined approach ensures that the dataset is not only more complete but also more diverse, which is essential for training models that generalize well to new, unseen data (Pourshahrokhi et al., 2022). Moreover, in fields where data collection is expensive or time-consuming, such as medicine, physics, and psychology, this strategy is particularly beneficial as it maximizes the utility of available data.

One study that effectively combined data augmentation and data imputation is by Vilardell et al. (2021), who investigated the efficacy of different methods for imputing missing data and generating synthetic data in breast cancer survival analysis. The study evaluated a range of models, including the ModGraProDep model, which integrates log-linear models with Bayesian networks, along with other techniques such as generalized linear models and neural networks. Using two different datasets and examining scenarios of missing data (MCAR and MNAR), the study found that the ModGraProDep models, particularly GM.SAT, consistently outperformed other methods. The inclusion of variables related to molecular subtypes further enhanced predictive

performance, confirming the effectiveness of ModGraProDep in both imputing missing data and enhancing data reliability in the context of breast cancer research.

Rath et al. (2023) proposed a novel model for handling missing data and enhancing training data in multivariate time series, particularly applicable to fields like plasma diagnostics. Their approach utilizes dependent state space Student-t processes, leveraging the correlation between input signals with a multivariate Matérn covariance kernel. This model accommodates heavy-tailed noise distributions, enhancing robustness to outliers. Through Bayesian filtering and smoothing, they reduce computational complexity, making it suitable for high-resolution time series. Evaluation on synthetic test cases inspired by plasma diagnostics data demonstrates improved accuracy in imputing missing data and generating augmented data compared to independent models that don't consider signal correlations.

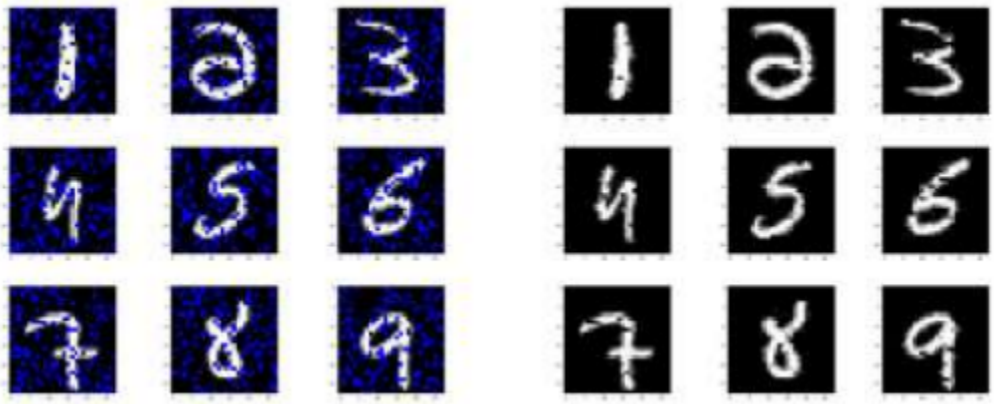

Figure 10. Image reconstruction of the MNIST dataset using F-HMC for imputing missing values (blue pixels) (Pourshahrokhi et al., 2021)

Another significant contribution comes from Pourshahrokhi et al. (2021), who introduced the Folded Hamiltonian Monte Carlo (F-HMC) model, combined with Bayesian inference, to effectively address missing data and preserve privacy by

augmenting the original data for research analysis. The F-HMC model works by adapting to the patterns in the existing data to create new samples, which can fill in missing information and enhance the overall dataset. This technique was tested on a dataset from the University of California, San Francisco (UCSF), which includes cancer symptom assessments with missing and sensitive data, as well as the Modified National Institute of Standards and Technology (MNIST) dataset. to illustrate that the proposed method is generalizable to other datasets as shown in figure 10. The study compared the F-HMC model's performance to standard methods like KNN and MICE using measures such as error rates and accuracy. The results indicated that the F-HMC model not only filled in missing values more effectively but also created higher quality synthetic data compared to other methods such as GANs and synthpop, especially in complex, high-dimensional datasets like those often found in healthcare, where other models often fail to perform well.

VI. Generative Adversarial Network (GAN)

Generative adversarial networks is one of the most extensively studied in the field of Artificial Intelligence, specifically deep learning, in the past few years. (Wang et al., 2021). Developed and proposed by Godfellow and his co-researchers, are a type of deep generative model that have been very popular for data generation, as it is capable of producing outputs that are very similar to its training data (Lee, J.,2022). Its ability to efficiently generate decision samples, elimination of possible bias and its compatibility with other neural networks makes it advantageous (Wang et al., 2021). Also, because of its ability to generate data without modeling the probability density function (Yi et al., 2019).

GANs consist of a unique class of neural network models where two networks undergo parallel training processes. One network concentrates on generation, while the other specializes in distinguishing generated data from real ones. This training scheme gained attention due to its usefulness in generating new samples. However, this concept is relatively new which is why it requires further research and different fields(Yi et al., 2019). The two networks, specifically, are the generator (G) and discriminator (D) wherein the discriminator is a binary classifier trained to differentiate between real data from the training set and fake data generated by the generator. While the discriminator improves its classification accuracy, the generator learns to produce data increasingly indistinguishable from real data, thus maximizing the discriminator's errors. (Lee, J, 2022).

The generator and discriminator of GAN are trained simultaneously in a min max manner where its goal is to find the optimal solution for both the generator and the discriminator, where the generator tries to generate realistic samples that can fool the discriminator, while the discriminator tries to distinguish between real and fake samples (Goodfellow et al., 2014).

$$min\, max\, V(G, D) \;=\; \Xi[log(D(x)] \;+\; \Xi[log(1 \;-\; D(z)]$$

Figure 11. Loss Function of GAN (Lee, 2022)

Figure above shows the minmax function where it operates such that the discriminator's goal is to maximize the probability of correctly classifying real samples as real (log(D(x))) and fake samples as fake (log(1 - D(G(z)))). While the generator's goal is to generate samples that can fool the discriminator into classifying them as real. The generator tries to minimize the term log(1 - D(G(z))), which means it wants the

discriminator to output a high probability for the generated samples being real. In short , its goal is to make discriminator maximize its capability to correctly classify samples, while generator minimize the ability of discriminator to classify generated data as fake (Lee, 2022).

Despite its advantages, GAN still proposes significant challenges in data generation such as generation of quality data, diversity of generated data and stabilizing training. (Wang et al., 2021). In addition, GANs are very difficult to train and evaluate due to the necessity for their discriminator and generator to achieve Nash equilibrium, which is very difficult during training. Additionally, there are instances where the generator fails to learn the full distribution of datasets, which usually leads to a mode collapse issue (Dai et al., 2017) Following are the reason why there is still a need for further research in this method especially on some forms of data that haven't fully explored yet (Lee, J, 2022).

1. Generative Adversarial Network Variants

A study proposes a taxonomy that divides different GANs into two main variants: the architecture variant and the loss variant. The architecture variants focus on modifications to improve the overall GAN architecture. On the other hand, the loss variant, which is further divided into two categories – loss types and regularization, involves optimizations or additions that penalize the loss function. After application of GAN into image generation, the result of the study shows that addition of self-attention to both generator and discriminator, as in SAGAN, enhances image diversity. For training stability, spectral normalization emerges as an effective, easy to implement, low-cost loss function solution. Current state-of-the-art models like BigGAN and PROGAN produce high-quality, diverse images in computer vision, but applying GANs to video and other

domains like time-series and natural language processing lags and presents opportunities for further research. (Wang et al., 2021).

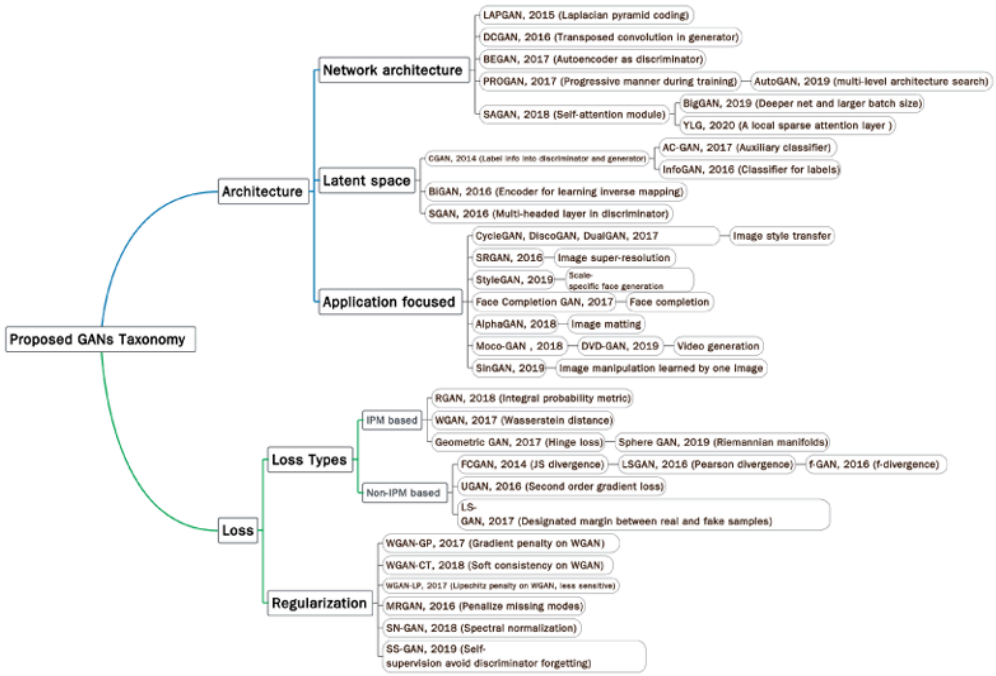

Figure 12.The taxonomy of the recent GANs (Wang et al., 2021)

GAN has been studied for applications in various types of data, including natural language generation, music generation, and images (Lee, J., 2022). These applications often focus on areas within computer vision, such as image generation, attribute manipulation, image translation, semantic segmentation, and many more (Wang et al., 2021).

A certain study proposed a GAN architecture, named MELGAN, which is used for conditional audio synthesis. MelGAN is non-autoregressive, fully convolutional, and shows significantly faster than real-time on GPUs and CPUs without optimization tricks. In the study, researchers successfully trained GANs for raw audio generation without adding any distillation or perceptual loss function which results in high-quality text-to-speech synthesis (Kumar et al., 2019).

Another study proposes a Transformer-based GAN approach for generating high-quality long symbolic music sequences. The model mainly uses a Transformer-XL as generator for modeling the long-term dependencies in music and a pre-trained BERT model as its discriminator network which provides feedback to the generator using training. Several techniques like the Gumbel-Softmax trick, truncated backpropagation through time (TBPTT), and gradient penalties are incorporated to stabilize the GAN on training of the discrete sequences. The result of the study shows that the method, with BERT Discriminator, performs better than the baseline models such as Transformar GAN with WGAN, Transformer GAN with WGAN GPen, with PPO-GAN and Transformer-XL (Muhamed et al., 2021).

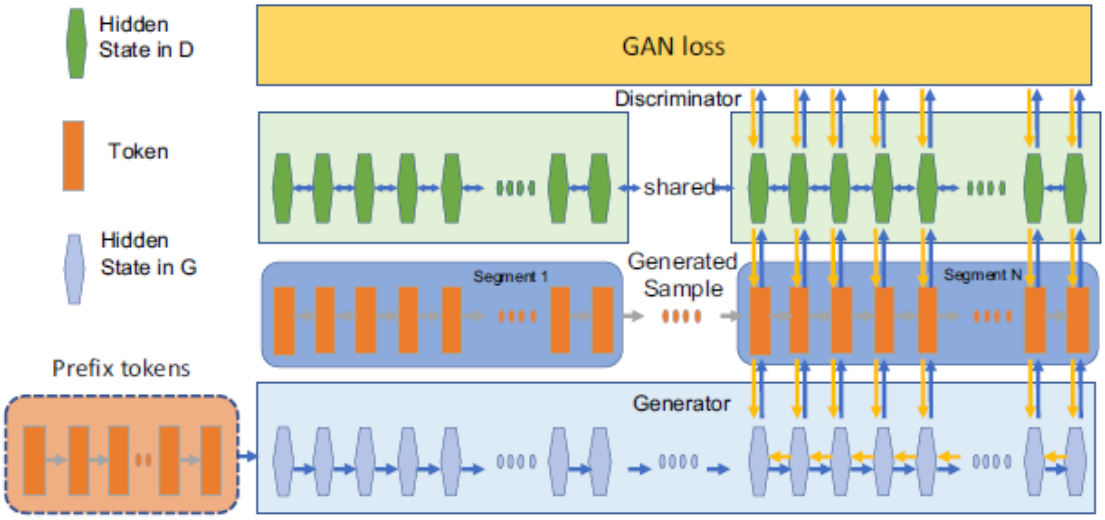

Figure 13. Transformer-based generative adversarial network (GAN) architecture (Muhamed et al., 2021)

Another GAN research, which proposes GAN-BERT extending the fine tuning process of BERT into two components such as generator G and a

discriminator D, taking the form of a semi-supervised GAN (SS-GAN) framework. Although it resembles the behavior of GAN entirely but since it uses unlabeled samples meaning that it has to deal with unsupervised loss components. Results reveal that text classification tasks like topic categorization, question classification and sentiment analysis showed that GAN-BERT can drastically reduce the needs for labeled samples. Reason is mainly because GAN-BERT achieved better performance with only 50-100 labeled examples than a fully supervised BERT model trained on much more data (Croce et al., 2020).

2. Generative Adversarial Network for Time Series Data

Although GANs have established their advantages in different forms of data, their application in generating synthetic temporal data, such as sequential and time-series data, is still relatively new. The G function and D function of it are almost similar, however the exact architecture of the models differs depending on the data feeded (Lee, J., 2022).

TimeGAN, or Time-series Generative Adversarial Networks, is another framework designed to generate realistic time-series data by preserving the temporal dynamics of variables over time. Introduced by Yoon et al. in 2019, this approach aimed to address the limitation of existing GAN methods for time-series generation, which do not adequately capture the temporal dynamics and correlations found in time-series data. TimeGAN integrates the flexibility of unsupervised GANs with the control of supervised training. It achieves this through a novel combination of an adversarial loss and a stepwise supervised loss, which ensures the model captures the conditional distributions of temporal transitions. Additionally, an embedding network reduces the high dimensionality

of the adversarial learning space, enhancing the learning of temporal relationships and improving parameter efficiency. Empirical evaluation of the study shows TimeGAN's superior performance over state-of-the-art benchmarks across various datasets. These results highlight the effectiveness of TimeGAN's supervised loss and embedding network in generating data that closely mimics real-world temporal dynamics. Future work may explore incorporating differential privacy to enhance its utility in sensitive data applications (Yoon et al., 2019)

A study by Niu and his colleagues in Beijing proposed an LSTM-based Variational Autoencoder Generative Adversarial Network (VAE-GAN) for time series anomaly detection. The method monitors equipment states using time series data, dividing the process into two stages: model training, where the model learns the normal data distribution, and anomaly detection, where anomalies are identified by calculating anomaly scores. The LSTM-based VAE-GAN jointly trains the encoder, generator, and discriminator to leverage their combined abilities for more accurate and faster anomaly detection. Experiments using the selected time series dataset showed that this method has a higher F1 value and spends less time compared to traditional GAN-based methods, due to the avoidance of the optimization process at the anomaly detection stage. While some points' anomaly scores are calculated multiple times due to the moving window mechanism, the accuracy remains unaffected. Despite its accuracy and speed, the method has limitations, particularly in detecting successive anomaly subsequences, which requires a redesigned anomaly score module. Future improvements include developing an adaptive threshold adjustment method for quicker use (Niu et al., 2020).

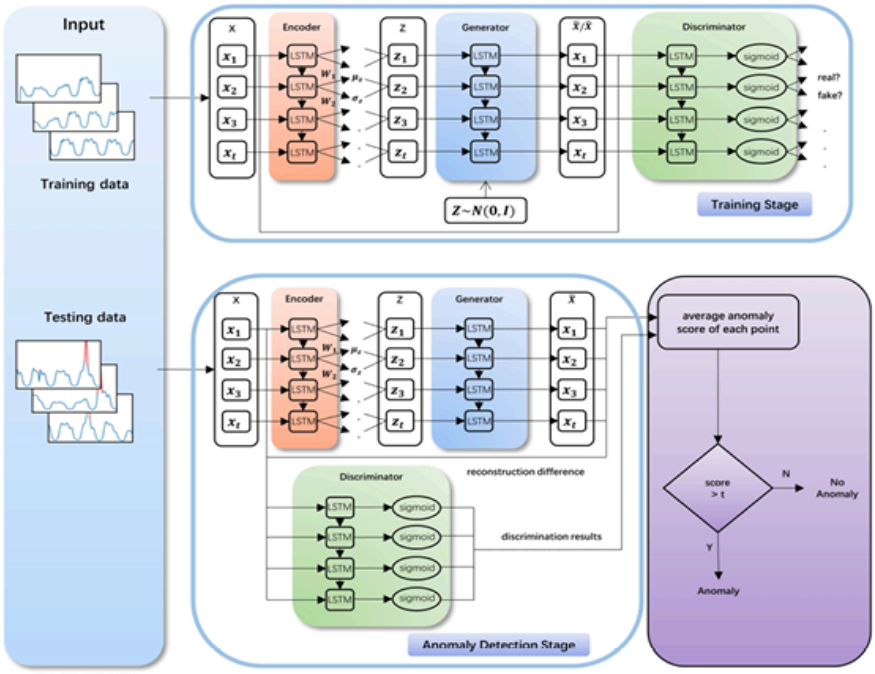

Figure 14. LSTM-based Variational Autoencoder Generative Adversarial Network Architecture (Niu et al., 2020)

Despite its accuracy and speed, the method has limitations, particularly in detecting successive anomaly subsequences, which requires a redesigned anomaly score module. Future improvements include developing an adaptive threshold adjustment method for quicker use (Niu et al., 2020).

Another study that focuses on Time series Data, proposed a Variational Recurrent Neural Network GAN (VRNNGAN), which is a novel GAN framework for synthetic time-series generation. It mainly uses Variational Autoencoder (VAE) as generator and incorporates the bidirectional RNN as a discriminator. With the recurrent VAE, temporal dynamics are captured and learned in the time varying latent space. The goal of the model is similar to different GAN frameworks, which is to generate realistic time-series data. Researchers uses three datasets and

perform mainly four evaluations, such as t-SNE Plots, Post-Hoc Discriminative Score, Post-Hoc Predictive Score and Percentile Score to test the performance of the model and the generated synthetic data (Lee, J., 2022).

The result shows that the VRNNGAN generates realistic synthetic data, particularly excelling in tasks measuring the usefulness of synthetic data in time-series modeling. VRNNGAN performed well in t-SNE plots and Predictive Score evaluations, often outperforming other baseline methods like TimeGAN. While its Discriminator and Percentile Scores were generally strong, VRNNGAN showed variable performance across different datasets, with some limitations on complex, multivariable data such as stock datasets. Comparatively, VRNNGAN often surpassed TimeGAN, VRNN, and CRNNGAN in most evaluations. However, VRNNGAN's training process is sensitive to hyperparameters, requiring careful tuning to optimize performance (Lee, J., 2022).

VII. Variational Autoencoder (VAE)

Variational Autoencoders (VAEs) are a type of generative model that share architectural similarities with traditional autoencoders. Both consist of an encoder (also called a recognition or inference model) and a decoder (or generative model), and they aim to reconstruct input data while learning from latent representations. The key distinction lies in how VAEs handle the latent space. Unlike regular autoencoders, VAEs create a continuous latent space. They achieve this by having the encoder output two vectors instead of one: a vector of means and a vector of standard deviations. The mean vector determines the central location of the encoded input, while the standard deviation vector defines the range of possible variations around that center. This design allows VAEs to sample encodings randomly within this range, exposing the decoder to different variations of the same input. This approach enables VAEs to capture more nuanced

representations of the data, making them powerful tools for tasks like data generation and imputation (Saldanha et al., 2022).

What sets VAEs apart is their ability in capturing and generating the underlying distribution of real data. This capability makes VAEs particularly suitable for generating synthetic tabular datasets. Their strength lies in using variational inference to learn the patterns and relationships within the real data. Once trained, a VAE can produce high-quality synthetic samples by drawing random noise from a Gaussian distribution and passing it through the decoder (Bang et al., 2024).

1. **Variational Autoencoder for Data Augmentation and Imputation**

There are studies that used a VAE for augmentation and imputation of data. The study of Paepae et al. (2023) aimed to evaluate the effectiveness of using a variational autoencoder (VAE) for data augmentation to enhance the prediction accuracy of nitrogen (N) and phosphorus (P) concentrations in water quality monitoring. The researchers used a VAE to generate synthetic water quality data and assessed the similarity between real and generated samples using distribution plots and Jensen-Shannon divergence. They then trained various machine learning models, including Deep Neural Networks (DNN), K-Nearest Neighbors (KNN), Extremely Randomized Trees (ERT), Support Vector Regression (SVR), and XGBoost (XGB), on both the original and augmented datasets. The results demonstrated that the VAE-generated data closely mirrored the distribution of the original data. Moreover, the predictive performance, measured by Root Mean Squared Error (RMSE), improved by 10-35% when the datasets were doubled using VAE-generated data. Among the models, KNN and ERT showed the best performance in urban and rural catchments, respectively. The researchers concluded that VAE-based data augmentation significantly enhanced the predictive accuracy of virtual sensors,

particularly in urban catchments. This approach allows for the use of fewer surrogate sensors while maintaining accuracy, which is advantageous for cost-effective water resource management.

On the other hand, the study of Boquet et al. (2019) addressed the problem of missing data in road traffic forecasting, which could negatively affect estimation accuracy. The authors proposed using a Variational Autoencoder (VAE) as an unsupervised data imputation method to learn the underlying traffic data distribution. They implemented a VAE with an encoder-decoder architecture to learn a continuous latent space that captured traffic data characteristics. The VAE was trained to minimize reconstruction error while regularizing the latent space. For imputation, missing values were initialized randomly, and the VAE iteratively refined the estimates until convergence. Using a real-world traffic dataset with induced missing data, they compared their VAE imputation against Principal Component Analysis (PCA) and a non-linear autoencoder (AE). The VAE significantly outperformed other methods, especially with Not Missing At Random (NMAR) patterns, showing up to 69.6% Root Mean Squared Error (RMSE) improvement in traffic speed forecasting.

2. Variational Autoencoder Variants

The study of Li et al. (2021) proposes a shift correction β-VAE (SC-β-VAE) model, a variant of the Variational Auto-Encoder (VAE), to address the imputation of specific missing values in multivariate time series data. The standard VAE assumes that training and test data follow the same distribution, which is often violated in real-world scenarios like meteorological or air quality data, where missing values are concentrated in specific periods. This concentration causes a shift in the original probability distribution, leading to decreased imputation performance.

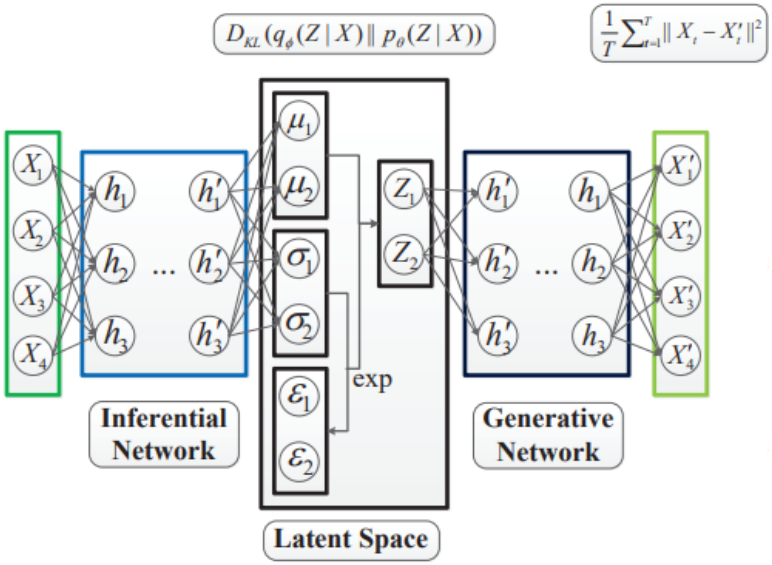

Figure 15. The network architecture of the standard VAE model (Li et al. 2021)

To address this, the authors introduce a shift correction hyperparameter λ to modify the latent space's Gaussian distribution from N(μ, σ) to N(μ + λσ, σ), correcting the deviated distribution. Additionally, they extend this to the β-VAE model, introducing a hyperparameter β to control the trade-off between the model's generative ability and disentanglement. The SC-β-VAE outperforms baseline methods, including statistical, machine learning, and generative models, in imputing specific missing values (Missing Not At Random) and random missing values (Missing Completely At Random) in real-world datasets. The study concludes that the SC-β-VAE effectively improves imputation accuracy by correcting the shifted probability distribution and balancing the model's generative and disentanglement abilities.

The study of Qiu et al. (2020) proposes using a variational autoencoder (VAE) framework for imputing missing values in genomic data, such as transcriptome and methylome data. They introduce a shift-correction (SC) variant of VAE to address scenarios where the missing values are drawn from a different

distribution than the training data, a common occurrence in certain missing data patterns.

In the SC-VAE, they modify the assumption of the training data distribution to follow a shifted Gaussian. This adjustment allows the model to better impute cases where missing values are concentrated at lower values. Their results demonstrate that for scenarios with missing values skewed towards lower expression levels, the SC-VAE achieves better imputation accuracy compared to traditional methods like K-nearest neighbors and singular value decomposition.

The authors also investigate the effect of varying the latent space regularization strength in VAE, showing that stronger regularization decreases imputation performance. They attribute VAE's imputation ability to the noise injection in the latent space, which is absent in regular deterministic autoencoders. This demonstrates that VAE, particularly the SC variant, can be an effective and computationally efficient alternative to traditional methods for imputing missing values in genomic data, especially in scenarios where missing data exhibits specific patterns.

Additionally, the authors explore the use of β-variational autoencoder (β-VAE), a generalization of VAE that introduces a hyperparameter β to balance the reconstruction loss with the regularization loss. When $\beta > 1$, the latent space is smoother and more disentangled, improving encoding efficiency. Conversely, when $\beta = 0$, the regularization term is removed, resembling a simple autoencoder with noise injected into the latent space. Experiments with varying β (0, 1, 4, 10) under different missing data scenarios (5%, 10%, 30%) show that imputation performance is similar for $\beta = 0$ and $\beta = 1$, while higher β values worsen performance. This suggests that strong regularization does not benefit imputation

tasks and that noise injection into the latent space is crucial for VAE's imputation ability.

VIII. Variational Autoencoder- Generative Adversarial Network (VAE-GAN)

Generative models are one way to synthesize time series data. Unlike random transformations that use random noise, slicing, cropping, or scaling, generative models take a less direct route and use the distributions of features in the datasets to generate new patterns (Iwana & Uchida, 2021). Some of the popular generative models include Variational Autoencoder (VAE) and Generative Adversarial Network (GAN).

These two generative models have their own strengths and weaknesses. For example, VAE uses the idea of probabilistic inference and reparameterization tricks to get various latent code z (Li, 2023). Meanwhile, GAN is a generative neural model based on a competition between two neural networks (Iglesias et al., 2023). The use of both generator and discriminator has made it possible for a GAN model to produce realistic data. However, these two have disadvantages such that VAE may be stable during the training process, but as it is being optimized to match the reconstruction loss of given inputs, it might produce blurry images (Ham et al., 2020). On the other hand, GAN is typically hard to train and they suffer from mode collapse, instability, and evaluation metrics (Iglesias et al., 2023). Due to this, balancing the generator and discriminator is difficult because in some instances, the discriminator converges faster than the discriminator (Ham et al., 2020).

In image processing, VAEs would typically produce blurred and low quality images since the input from the encoder only uses a simple element-wise error, however, humans see images in its high feature form.

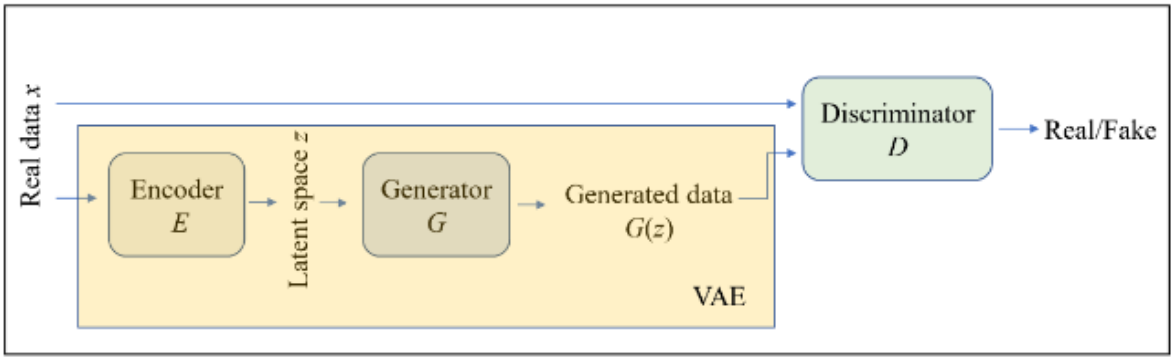

Figure 16. VAE-GAN Architecture (Ruan et al., 2023)

On the other hand, GANs would be able to generate sharp images while also capturing important features from it. However, training of a GAN model would be difficult because the generator learns from a random distribution of z, and its loss function depends on the discriminators. The quality of the images will start to degrade if the generator will be able to fool the discriminator and its ability to classify the real ones from the fake one is nearly 50%, the discriminator might accept strange generation results. To solve this problem, combining the strengths of these two generative models have been proposed over the years. As seen in Figure 16, VAE-GAN utilizes the latent variable model of VAE to generate the data and uses the discriminator of GAN to evaluate the authenticity of the generated samples (Ruan et al., 2023). It uses an encoder to input the data into the latent space, and the encoded latent vector will be used as an input for the decoder or generator. The data reconstructed by the decoder will be used as an input for the discriminator where it will determine whether the generated data is real or fake. A loss function will be used for cross-learning between the two networks, which will improve the generative power of the model (Hu et al., 2023). This combination would allow the model to enhance its generative capabilities by generating more high quality and diverse samples of time series dataset.

1. Variants of VAE-GAN

VAEGAN was first proposed by Larsen et al. in 2015 where it uses an end-to-end architecture that is configured in the order of encoder, decoder, and discriminator (Ham et al., 2020). And for the past years, there have been several studies conducted where novel approaches and hybrid models were developed.

For instance, in the study of Ye and Bors (2020), they developed a model capable of learning new tasks without forgetting the previously known knowledge while also retaining meaningful and disentangled representation of data. The Lifelong VAEGAN (L-VAEGAN) is a hybrid model following the lifelong learning framework and VAEGAN architecture. It addresses the gap of Generative Replay Mechanism (GRM) where it is capable of learning multiple tasks while keeping previously learned knowledge using generative models like GAN or VAE, but lacks the ability to learn latent data representation. A two-step optimization algorithm called “wake” and “dreaming” were used to train the hybrid model. This was applied to supervised, semi-supervised, and unsupervised learning. Under supervised learning, L-VAEGAN was trained to learn MNIST to SVHN and MNIST to Fashion lifelong learning tasks. The results of their experimentation showed that L-VAEGAN achieved higher accuracy compared to state-of-the-art models such as LGAN. Meanwhile, training L-VAEGAN under semi-supervised learning where only a small number of labeled data from different databases were considered. There were 1,000 labelled images considered for MNIST dataset, while 10,000 images were considered for Fashion database. The results of their experimentation showed that in a semi-supervised setting, the proposed model outperformed LGAN and has a competitive results compared to other models. Lastly, the training of L-VAEGAN in an unsupervised setting showed that the proposed model could learn multiple tasks while keeping previously known

knowledge. Their experimentation showed that L-VAEGAN was able to smoothly interpolate images coming from different sources. Such that, the proposed model was able to transition from a chair to a human face. This could mean that L-VAEGAN could learn from multiple domains while keeping a meaningful latent representation of data without having a catastrophic forgetting.

In another study by Ham et al. (2020), they proposed a model called Unbalanced GAN where it uses VAE as a pre-trained generator to balance the convergence between the GAN's generator and discriminator. First, an input of the dataset was fed to the VAE model and the value of the weights of its decoder will be used to initialize the generator. And the latter was trained using a GAN loss function. A pre-trained generator using VAE was employed to address the issue of mode collapse and to ensure that the GAN model would not converge to a strange distribution. In their experimentation, the proposed model was compared to other GAN models including DCGAN, LSGAN, and WGAN. They used three different datasets namely MNIST, CIFAR-10, and LSUN Bedroom. The results of their experimentation showed that the proposed model outperforms other models in terms of inception score. The latter is a performance metric used to measure the quality and diversity of the generated images.

Chen et al. (2023) proposed D-VAEGAN model to classify DeepFake images by using denoising and VAEGAN framework. Adversarial attacks can bypass current DeepFake detection systems by adding perturbation to the images that are typically not noticeable by the human eyes, hence training an adversarial model such as VAEGAN was proposed to combat this. The generator, VAE was used to remove the perturbations from the images, while the discriminator was used to classify whether the reconstructed image is real or fake.

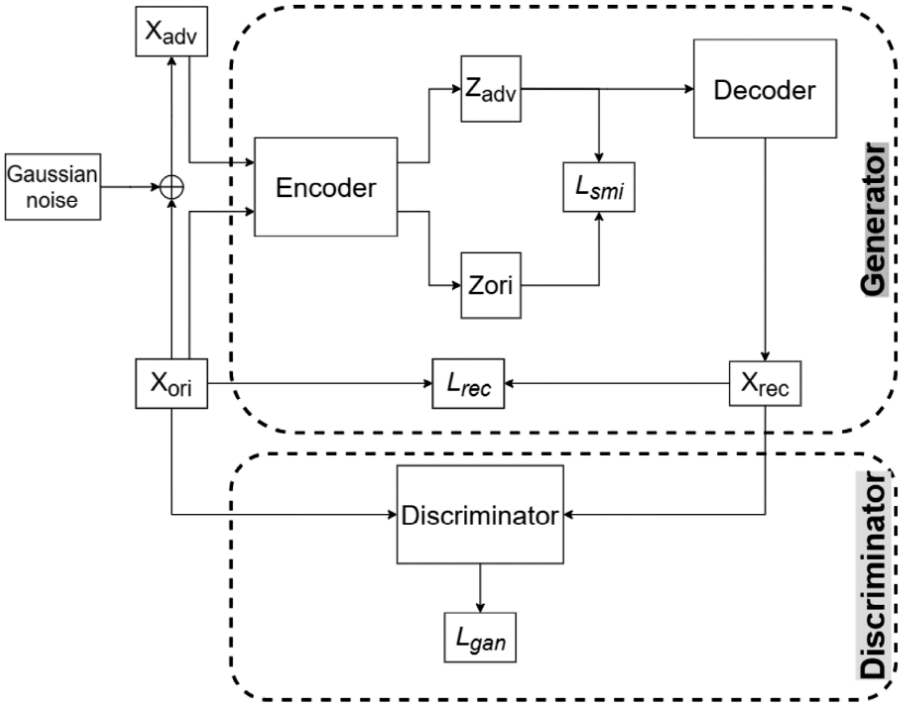

Figure 17. D-VAEGAN Architecture (Chen et al., 2023)

In the figure above, first, an input of clean image z and adversarial example z′ were used as an input to the encoder where z′ used a denoising technique to remove the perturbation effects from the images. Then using this, features will be mapped out in the latent space and be used by the decoder to reconstruct the images. Loss functions were used to measure the similarity between the original and reconstructed image. Then the output from the decoder will be used as an input for the discriminator to classify whether the reconstructed image is real or fake. An adversarial loss is measured to ensure that the generative capability of the generator is derived from the discriminator loss. Their experimentation included testing this to adversarial attacks such as FGSM, BIM, PGD, DeepFool, and C&W. The results showed that the proposed model yielded robustness in terms of classifying DeepFake images.

2. VAE-GAN for Synthetic Data Generation

In a study by Lee (2022), he proposed a novel VAEGAN model called VRNNGAN for generating time series synthetic data. It uses the GAN framework where the generator uses a recurrent VAE, and a bidirectional RNN was used as the discriminator. The VRNN is the generation G function, while bidirectional RNN is the discriminator D function. In the G function, the VRNN model has the capability to reconstruct and generate time series data. The real sample, labeled as “real”, along with the reconstructed and generated sample that derived from the inference and generation model respectively, labeled as “fake” were fed to the D function where it has a strong capability of classifying which data is real or fake. A loss function was measured to ensure the balance between the generator and discriminator. In the experimentation, the proposed model was evaluated using three different time series datasets namely ARMA, ECG200, and Stocks. The results of the experimentation showed that the model performed well in different performance metrics such as t-SNE plots where the plots between the synthetic data and original data overlapped in the same area. Meanwhile, only the ECG dataset had the lowest Post-Hoc Discriminative Scores while TimeGan and VRNN performed much better in ARMA and Stocks datasets respectively. On the other hand, the proposed model yielded good results for both Post-Hoc Predictive Score and Percentile Scores. This shows that VRNNGAN is capable of generating synthetic data, however, further improvements might be needed.

The study of Zhang et al. (2023) used VAEGAN to generate synthetic data for sea-land clutter classification of sky-wave-over-the-horizon radar (OHTR). Since deep learning models usually need a large amount of data, class imbalance and scarce data are common problems for sea-land clutter classification of OHTR. To address this problem, an auxiliary classifier was

introduced to the VAEGAN architecture, and an AC-VAEGAN model was developed. Unlike typical VAEGAN, the proposed model can specify the class of the synthetic data. The AC-VAEGAN is composed of three parts, namely En, De/G, and D/C. The En is responsible for encoding the data to the latent space, and the output (z_deco) from this is used as an input for the De/G. The latter not only takes z_deco, but it also takes its attribute c as an input, along with random noise vector z_gen and its class attribute c. The loss function for both generator and discriminator is also computed. In their experimentation, they used a benchmark dataset for sea-land clutter of OHTR, and validated it using the MSTAR dataset. The results of their experimentation showed that AC-VAEGAN outperforms AC-GAN in both traditional GAN metrics such as GAN-train and GAN-test, and statistical evaluation including absolute distance (AD), cosine similarity (CS), and Pearson correlation coefficient (PCC). However, it had some limitations such as the loss function lacks an interpretable indicator that can guide the training process of the model.

Synthesis of the Reviewed Literature and Studies

The studies reviewed underscore the importance of handwriting data, particularly in online analysis, for its ability to capture unique features inaccessible through offline methods. Online handwriting data has shown notable performance, especially with deep learning networks, but to achieve effectiveness, large datasets are necessary. Additionally, due to the limitations in recording in-air features with current stylus and tablet technologies, there is often missing data, thereby impacting the integrity of the analysis.

Literatures have supported that to increase dataset size, data augmentation is a more practical method than creating new data from scratch. Efforts to address the issue

of low dataset sizes through augmentation encounter challenges, primarily relying on traditional methods that necessitate expert label maintenance and oversight. Moreover, while time series data augmentation techniques are prevalent, they have largely overlooked the nuances of multivariate datasets like handwriting data. Nonetheless, studies have suggested that by combining various methods and promising advancements in deep generative models, there is potential to generate realistic synthetic handwriting samples. These advancements could help extend these models to better handle time series data modeling for high-dimensional, multivariate datasets.

However, imputation techniques specifically for handling missing in-air features in online handwriting data remain underexplored. Existing imputation methods prove ineffective, especially when dealing with data missing completely at random which is often more reflective of real-life scenarios. Consequently, there exists a notable gap in the research around developing imputation techniques tailored to effectively handle missing data in such high-dimensional, multivariate time series datasets while preserving the integrity of the recorded samples.

Despite the advancements of generative adversarial networks (GANs), they still face significant limitations in effectively modeling complex multivariate time series distributions. While recent studies have shown promising results in using GANs to generate synthetic time-series data, challenges remain in optimizing hyperparameters and ensuring robust performance across diverse datasets and applications.

Current VAE-based imputation methods show promise for handling missing data in various domains. However, their effectiveness in imputing missing values in time series data remains a challenge. One notable limitation is the assumption that training and test data follow the same distribution, which is often violated in real-world scenarios. This discrepancy leads to decreased imputation performance, especially when missing values are concentrated in specific periods, causing a shift in the original probability

distribution. In addressing this issue, recent studies propose innovative approaches such as the shift correction β-VAE (SC-β-VAE) model. This variant of VAE introduces a shift correction hyperparameter to modify the latent space's Gaussian distribution, effectively correcting the deviated distribution caused by missing values.

Recent studies have started combining Variational Autoencoder (VAE) and Generative Adversarial Network (GAN) to leverage the latent variable model of VAE and the discriminative power of GAN for improving the quality and diversity of generated data. Despite their successful application in synthetic data generation across various domains, there is currently no exploration, based on the author's reviewed studies, of their potential for imputing missing values in multivariate time series data.

Based on these findings, the current study explores the use of the shift correction mechanism to effectively address the distributional shifts caused by missing data, which is a common issue in online handwriting datasets. This mechanism will be incorporated into a VAE-GAN model, combining the strengths of both VAEs and GANs. VAEs excel at learning robust representations of complex data distributions, while GANs are adept at generating high-quality synthetic samples. Unlike many existing imputation and augmentation methods designed for univariate data, the proposed model is specifically tailored to handle the complexities of multivariate time series data, such as handwriting. By generating synthetic data that closely mimics the characteristics of the original handwriting data, the proposed model aims to offer an inexpensive, time-efficient method to address the challenges posed by limited and missing data in handwriting datasets, potentially leading to improved performance in various handwriting analysis tasks. Additionally, to better demonstrate the effectiveness of the proposed model, three types of baseline models—VAE-GAN, TimeGAN, and VRNNGAN—are selected for comparative experiments.

Chapter 3

METHODOLOGY

Research Design

The study will implement a quantitative quasi-experimental design to evaluate the effectiveness of models based on the augmentation and imputation techniques used. In this design, it is expected that changes in the independent variables will lead to changes in the dependent variables. The independent variables in this study are the imputation and augmentation models, including VAE-GAN, TimeGAN, VRNNGAN, and the proposed SC-β-VAE-GAN. These models will be assessed in generating synthetic data for two distinct datasets: EMOTHAW and GPS time series data from Greenland. The evaluation will be based on several dependent performance metrics, including Normalized Root Mean Square Error (NRMSE), Post-Hoc Discriminative Score, and Post-Hoc Predictive Score.

The quasi-experimental design does not require the use of control and experimental groups, nor does it rely on randomization. This design is well-suited for this study because it does not require the establishment of control and experimental groups, and there is no need to randomly assign participants to different treatments or conditions. Instead, the study utilizes pre-existing datasets that were not collected through a randomized process, rendering randomization unnecessary. The focus is on assessing the impact of different imputation and augmentation techniques on the effectiveness of the models.

Sources of Data

To conduct the study, an essential requirement is a handwriting multivariate time series dataset. The researchers will augment and impute the EMOTHAW dataset, a novel and publicly available database developed by Likforman-Sulem et al. (2017) for

recognizing emotional states through handwriting analysis. The EMOTHAW dataset consists of handwriting samples from 129 participants, all of whom are Master's and BS students from the Department of Psychology at the Seconda Università di Napoli in Italy. The participants' ages range from 21 to 32 years, with a mean age of 24.8 years.

The database includes seven tasks: drawing interlinking pentagons, drawing a house, writing four Italian words in capital letters, drawing loops with both hands, performing the Clock Drawing Test, and writing a phonetically complete Italian sentence in cursive. These tasks were carefully chosen based on well-established medical and psychological tests used for cognitive impairment detection and personality assessment.

To collect the data, Likforman-Sulem used an INTUOS WACOM series 4 digitizing tablet and an Intuos Inkpen. This setup allowed them to capture not only the on-paper handwriting but also in-air movements, which have proven to be as important as on-surface information in previous studies. The tablet recorded various parameters for each data point, including x-y positions, timestamps, pen status (up or down), pressure, and pen azimuth and altitude angles.

In addition to the handwriting tasks, each participant completed the Italian version of the Depression Anxiety Stress Scales (I-DASS-42) questionnaire. This self-report tool assesses the levels of depression, anxiety, and stress experienced by the participants over the past week, providing ground truth labels for the handwriting data. The researchers have already contacted the authors and successfully obtained the EMOTHAW dataset. The handwriting data is in SVC file format and the I-DASS-42 data is in xls file format.

The researchers will also use the Greenland GPS dataset for the validation of the proposed SC-β-VAE-GAN model, which was also used in the study of Zhang et al. (2021) to impute data. It is a dataset from Nevada Geodetic Laboratory, the University of Nevada at Reno. The dataset consists of daily GPS coordinate time series from 20

stations in Greenland wherein stations provide data for geodetic and geophysical studies, but due to logistics challenges and hardware malfunctions, especially in harsh polar environments like Greenland, these time series often contain gaps or missing values. The dataset is useful for validation purposes as it represents real-world time series geospatial data with natural occurrences of missing values, making it an ideal for evaluating the ability of the proposed model to handle and accurately impute missing data in time series.

Research Instrument

The researchers will develop a tool to impute and augment data based on the VAE-GAN framework. To address the research question, it is essential to validate the tools used. Additionally, the researchers will follow a step-by-step procedure detailed in the experiment paper, which will cover data preparation, model evaluation, and comparison with existing models.

The primary programming language utilized for developing the experimental framework is Python, chosen for its extensive libraries and frameworks tailored to machine learning and data processing needs. Complementing Python, Visual Studio Code (VS Code) is employed for code development and execution as it provides a robust and versatile development environment that supports data exploration, visualization, and comprehensive documentation of the experimental process.

On the other hand, for data processing, especially for time series data, the researchers will utilize key Python libraries such as Pandas for data manipulation and analysis, NumPy for numerical computations, Matplotlib and Seaborn for data visualization, and TSFresh for extracting relevant features from time series data.

The experiment paper includes detailed procedures, tables, and tools necessary for recording and evaluating the results of the generated synthetic data. This document

ensures a systematic approach to the experimentation process and provides a clear framework for assessing the performance and quality of the results.

System Architecture

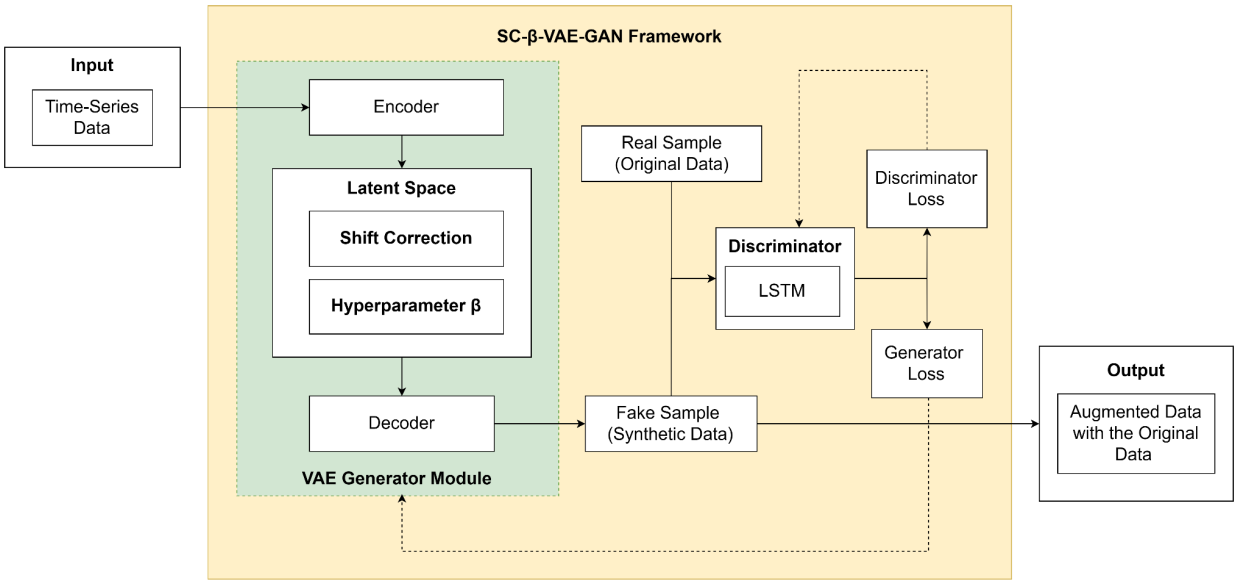

Figure 18. System Architecture of SC-β-VAE-GAN for Generating Synthetic Data for Imputation and Augmentation

The SC-β-VAE-GAN framework is designed to augment and impute multivariate time-series data. The process begins with the input of time-series data, which is fed into the VAE Generator Module. This module consists of an encoder, a latent space with shift correction and hyperparameter β, and a decoder. Initially, the encoder processes the time-series input data, compressing it into a lower-dimensional latent space representation. Within this latent space, a shift correction mechanism adjusts the latent variables, while the hyperparameter β controls the degree of regularization in the VAE. The decoder then takes this processed latent space representation and generates synthetic data intended to closely resemble the original time-series input data.

The synthetic data generated by the VAE Generator Module is then passed to the Discriminator Module, which includes an LSTM-based discriminator. This discriminator

distinguishes between real and synthetic data. The real time-series input data is labeled as a real sample, while the synthetic data generated by the decoder is labeled as a fake sample. The discriminator evaluates both real and fake samples, outputting a discriminator loss that reflects how accurately it can differentiate between the two. Concurrently, the framework calculates two types of losses: the discriminator loss and the generator loss. The discriminator loss is incurred when the discriminator incorrectly classifies real and fake samples, while the generator loss is based on the generator's ability to produce synthetic data that can fool the discriminator.

The framework operates within an adversarial training loop, where the synthetic data generated by the VAE generator is continuously improved by minimizing the generator loss. Simultaneously, the discriminator is trained to maximize the discriminator loss, thereby enhancing its ability to distinguish real data from synthetic data. This iterative process continues until the synthetic data becomes indistinguishable from the real data. The final output of the SC-β-VAE-GAN framework is augmented data, which comprises both the original time-series data and the high-quality synthetic data produced by the VAE generator. This augmented data can subsequently be utilized for various downstream applications, such as training machine learning models, thus demonstrating the effectiveness and utility of the SC-β-VAE-GAN framework in enhancing original datasets for improved analysis and model performance.

Data Gathering/Generation Procedure

The following steps will be followed by the researchers in generating the data:

1. The researchers will collect the handwriting samples from the public database, EMOTHAW. This will undergo pre-processing where the data will be sorted and organized by handling missing values and normalizing the data.

2. After pre-processing, the dataset will be fed to the SC-β-VAE-GAN model, following the GAN framework, where VAE will act as a generator, and a Long Short-Term Memory (LSTM) network will be the discriminator.
    a. The inferential network or encoder will input the dataset to the latent space. A Gaussian Distribution will be used to map the probability distribution of the dataset in the latent space. Then, using a Gaussian Distribution with shift correction where the same mean and variance will be used to sample the latent vector Z. The mean will be modified by adding a shift parameter multiplied to the variance. This will be used to ensure that the model could make an assumption close to the original probability distribution as much as possible when learning input data with missing values.
    b. A hyperparameter β will be used to control the trade-off between the generation and disentanglement of the data. If β=1, it will follow a standard VAE model, if β>1, the regularization degree will increase, making the probability distribution smoother, and disentanglement stronger, however degrading the quality of generating data. If β=0, there is no regularization and there is only a loss function and reconstruction of the data. And if 0<β<1, the β-VAE model will balance the regularization and reconstruction term for better generation and disentanglement of data. This is to make sure that the model will generate a better data imputation.
    c. Adding these two hyperparameters would allow the model to have a better learning of the handwriting dataset that has been inputted. A latent vector Z will be sampled using the adjustments in the latent space. Next, using this as an input, the generative network

or decoder will reconstruct the handwriting time series dataset where synthetic data will be generated.

d. Using the synthetic data and the real sample data, these two will be fed to the LSTM discriminator where it will classify if the synthetic data generated is real or fake.

e. A loss function for both generator and discriminator will be computed. The former will be used to measure how well the generated samples are close to the real ones by making the discriminator believe that they are real. Meanwhile a discriminator loss will measure how well the LSTM distinguishes between real and fake samples.

3. The performance of the model in generating synthetic data will be evaluated using Normalized Root Mean Square Error (NRMSE), Post-Hoc Discriminative Score, and Post-Hoc Predictive Score.

Ethical Consideration

To ensure ethical conduct, the researchers will obtain ethical approval first from the ethics committee at the Polytechnic University of the Philippines before conducting the study. The study will use the datasets EMOTHAW and Greenland GPS, and will ensure appropriate use by strictly adhering to the terms and conditions specified by the dataset providers. The researchers will give proper credits to the authors of the original datasets and comply with data protection regulations. Maintaining anonymity and confidentiality is a priority. All personally identifiable information will be anonymized. Transparency will be ensured throughout the study by thoroughly documenting the methods, data preprocessing steps, model training procedures, and evaluation metrics.

Research findings, including negative results, will be reported transparently, providing an honest account of the research process.

Analysis and Statistical Treatment of Data

The following data treatment was used to solve the statement of the problems of this study, as well as to analyze the result of the model performance and its comparison to other imputation and augmentation methods.

1. **Normalized Root Mean Square Error (NRMSE)**

   This metric is used to measure the average discrepancy between the synthetic data generated by SC-β-VAE-GAN and the real data, normalized by the range of the observed data. This metric provides evaluation of the model's accuracy, with lower NRMSE values indicating high performance.

   Each data consist of sequence of data points over time, definite Y_i be the observed value at the i-th point, which can be a vector including the features $Y_i = (x_i, y_i, p_i, \theta_i)$ and $\widehat{Y}_i$ be the predicted value (synthetic data) at the i-th time point which is $\widehat{Y}_i = (\widehat{x_i}, \widehat{y_i}, \widehat{p_i}, \widehat{\theta_i})$. The computation of error for each are computed by $Error_{f,i} = y_{f,i} - \widehat{y}_{f,i}$. Then RMSE is calculated for each feature across all time points.

   Calculate the Root Mean Square Error (RMSE) is calculated using the formula:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (Y_i - \widehat{Y}_i)^2}{N}}$$

To normalize the RMSE and make it comparable across different data, the NRMSE is computed by dividing the RMSE by the mean of the observed values.

$$NRMSE = \frac{RSME}{mean(y)}$$

A lower NRMSE indicates that the generated synthetic data closely resembles the real data, reflecting the model's strong performance in accurately capturing the characteristics of the handwriting samples. This suggests that the model is effective in learning and reproducing the underlying patterns and features of the original data, making the synthetic data highly realistic. Conversely, a higher NRMSE suggests that the synthetic data deviates significantly from the real data, highlighting areas where the model may need further refinement and improvement. This indicates that the model is less effective in replicating the true characteristics of the handwriting samples, resulting in synthetic data that is less realistic and potentially less useful for subsequent analysis or applications. The results for the models will be summarized by calculating the mean and standard deviation to facilitate comparison with other models.

2. Post-Hoc Discriminative Score

In the Post-Hoc Discriminative Score task, an LSTM model is trained to classify data as either real or synthetic. The goal is to achieve a classification accuracy of 50%, which indicates that the classifier cannot distinguish between the real and synthetic data. This outcome would mean that the synthetic data is

effectively indistinguishable from real-world data, demonstrating its validity as real-world data.

Researchers begin by combining the real and synthetic data into a single dataset. Then a 10-fold cross-validation approach is performed to ensure the reliability of the results, with nine folds used for training and the remaining fold for testing. To evaluate the results, the accuracy must be around 50%. The classifier can achieve this 50% accuracy in the following ways:

- Correctly identifying all real data and incorrectly identifying all synthetic data.
- Incorrectly identifying all real data and correctly identifying all synthetic data.
- Correctly identifying some real and some synthetic data, while incorrectly identifying others, such that the total correct guesses amount to 50%.

The main objective is to produce synthetic data such that the performance of the binary classifier is comparable to that of a random classifier. If the classifier achieves 100% accuracy, it means the synthetic datasets have failed to generate realistic data. This leads to the interpretation that the lower the discriminative score, the more realistic the synthetic data, while a higher score indicates a lack of realism. The results for the models will be summarized by computing the mean and standard deviation for easier comparison with other models.

3. Post-Hoc Predictive Score

The Post-Hoc Predictive Score measures the prediction accuracy of synthetic data generated by a model. To evaluate this, all synthetic data is used, with the last time step of each sample set aside as the prediction target, and all

previous time steps used as input for the model. The model is then tested on real data, serving as the ground truth holdout set. Min-max scaling is applied to normalize the data, with each experiment repeated 10 times to ensure consistency and validation.

The Mean Absolute Percentage Error (MAPE) is used to evaluate the model's performance in predicting the last time step. Additionally, MAPE is calculated as the average of the absolute percentage errors between the actual and predicted values. The Mean Absolute Percentage Error (MAPE) is used as the predictive score:

$$MAPE = \frac{\sum_{i=1}^{N} \left(\frac{Y_i - \widehat{Y}_i}{Y_i}\right) x\ 100}{N}$$

To interpret the result, lower MAPE indicates that the synthetic data accurately captures the patterns of the original data, while higher MAPE suggests poor predictive performance. For each model, the mean and standard deviation of MAPE are computed to aid in visualization and comparison, providing a clear assessment of how well the synthetic data generated by the proposed technique preserves the predictive characteristics of the original dataset from different models.

4. Hypothesis Testing

The Chi-square test was employed to examine whether there exists a significant difference in the performance of synthetic data generation among various models, specifically, SC-β-VAE-GAN compared to other models, namely, VAE-GAN, TimeGAN, and VRNNGAN based on the result of the computed

performance metrics results, specifically Normalized Root Mean Square Error, Discriminative Score, Predictive MAPE Score. The formula of the Chi-Square is:

$$\chi^2 = \sum \frac{(O_i - E_i)^2}{E_i}$$

Where:

X^2 = Chi-Squared

O_i = Observed Output (Proposed Model Performance)

E_i = Observed Output (Baseline Model Performance)

Computing for the chi-square test will determine the p-value. A p-value of 0.05 or less (p 0.05) is regarded as significant, indicating that the null hypothesis (Ho) is rejected. However, a p-value greater than 0.05 (p > 0.05) is not statistically significant, implying that the null hypothesis (Ho) is accepted.

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APPENDICES

Appendix 1: Experiment Paper

Objective:

The objective of the experiment is to answer the Statement of the Problem.

Materials and Equipment:

- The developed SC-β-VAE-GAN model for generating time-series synthetic data.
- The two datasets:
    - EMOTHAW dataset
    - GPS Time Series Data
- Experiment Paper
- Pen and Paper

Procedure:

1) Researchers will prepare an experiment paper to serve as a guide for evaluating the developed system.
2) Then researchers will generate synthetic data for the given data set, specifically with EMOTHAW dataset.
3) After generating and iterating on the data, the performance of the proposed model, SC-β-VAE-GAN, in generating synthetic data will be evaluated using metrics such as Normalized Root Mean Square Error (NRMSE), Post-Hoc Discriminative Score, and Post-Hoc Predictive Score.

4) The evaluation will also be repeated with other baseline models, including VAE-GAN, TimeGAN, and VRNNGAN, with the results documented in the following table:

Evaluation of Normalized Root Mean Square Error

Normalized Root Mean Square Error		
Model	EMOTHAW Dataset	
	Mean	**Std.**
VAE-GAN		
TimeGAN		
VRNNGAN		
SC-β-VAE-GAN		

Evaluation of Post Hoc Discriminative Score

Discriminative Score		
Model	EMOTHAW Dataset	
	Mean	**Std.**
VAE-GAN		
TimeGAN		
VRNNGAN		
SC-β-VAE-GAN		

Evaluation of Post Hoc Predictive Score

Predictive MAPE Score		
Model	EMOTHAW Dataset	
	Mean	**Std.**
VAE-GAN		
TimeGAN		
VRNNGAN		
SC-β-VAE-GAN		

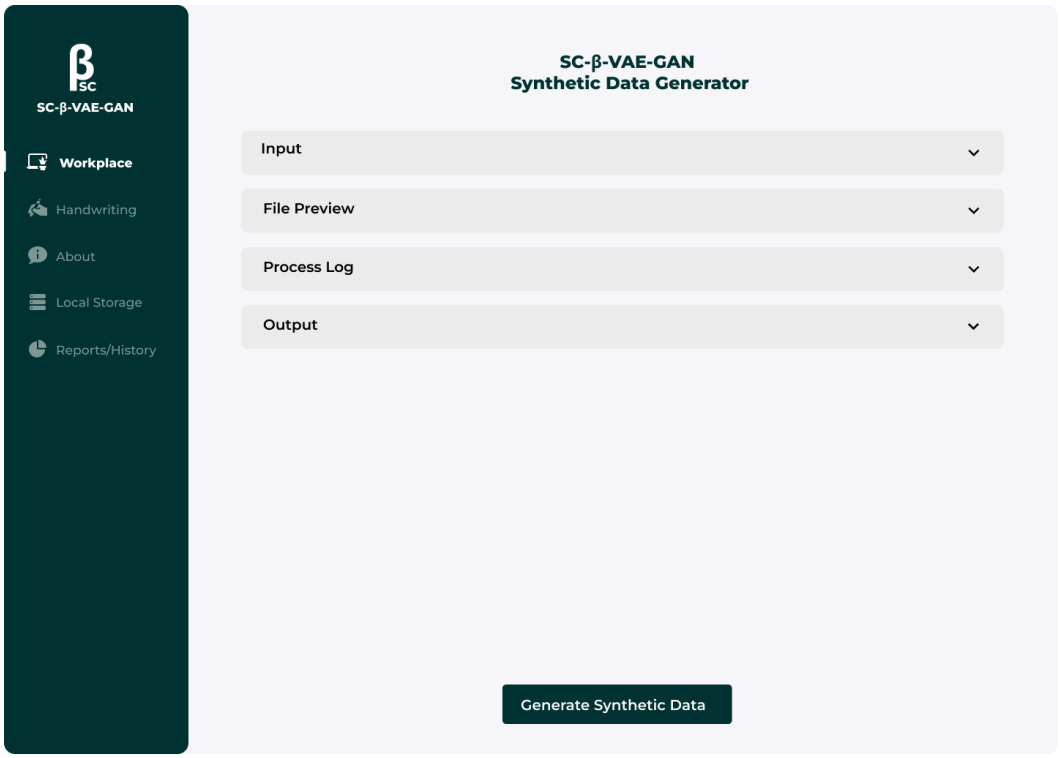
5. To address the hypothesis, a Chi-Square will be used between the metric results of the proposed model and other baseline models, specifically VAE-GAN, Time-GAN, and VRNNGAN.

Hypothesis Testing

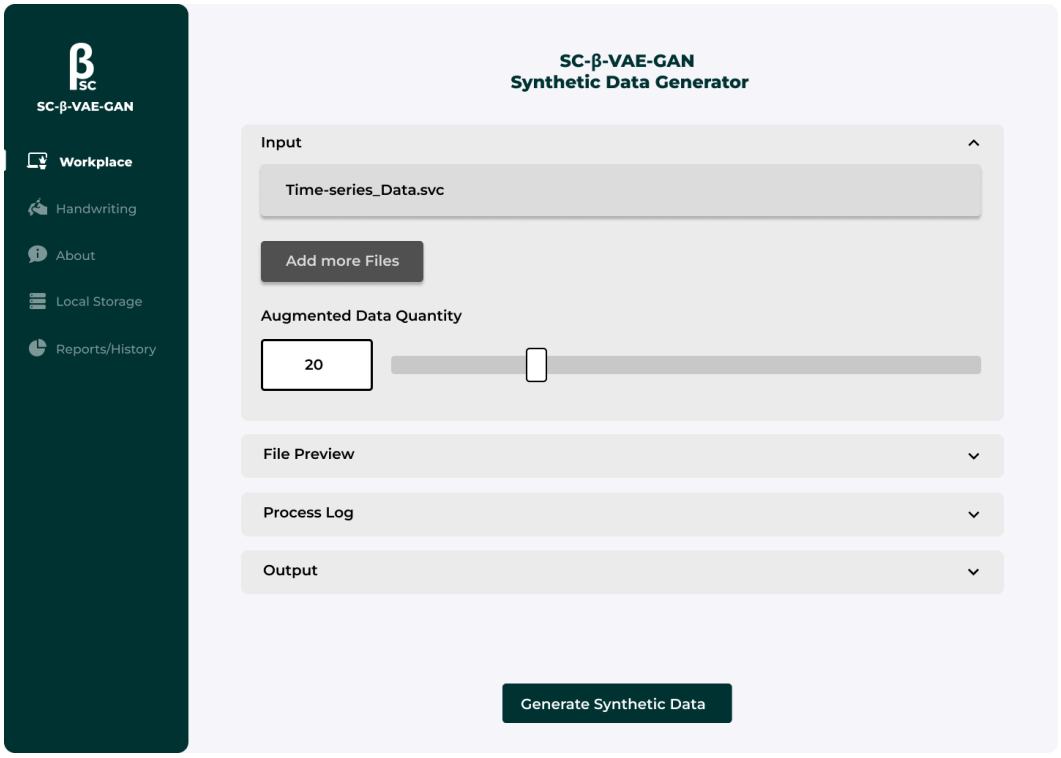
HYPOTHESIS TESTING					
	HYPOTHESIS	**NRMSE**	**Discriminative Score**	**Predictive Score**	**Conclusion**
H0	SC-β-VAE-GAN				
	VAEGAN				
H0	SC-β-VAE-GAN				
	TimeGAN				
H0	SC-β-VAE-GAN				
	VRNNGAN				

Appendix 2: Initial Mockup Design

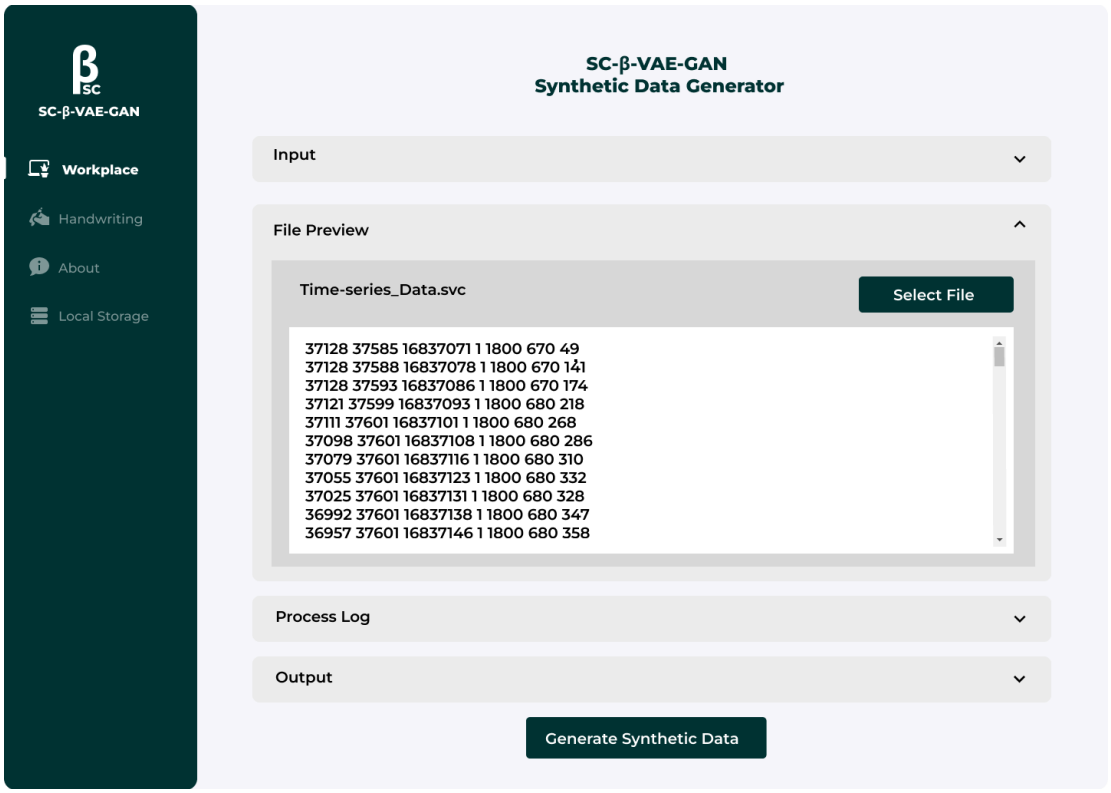
SC-β-VAE-GAN Main Page



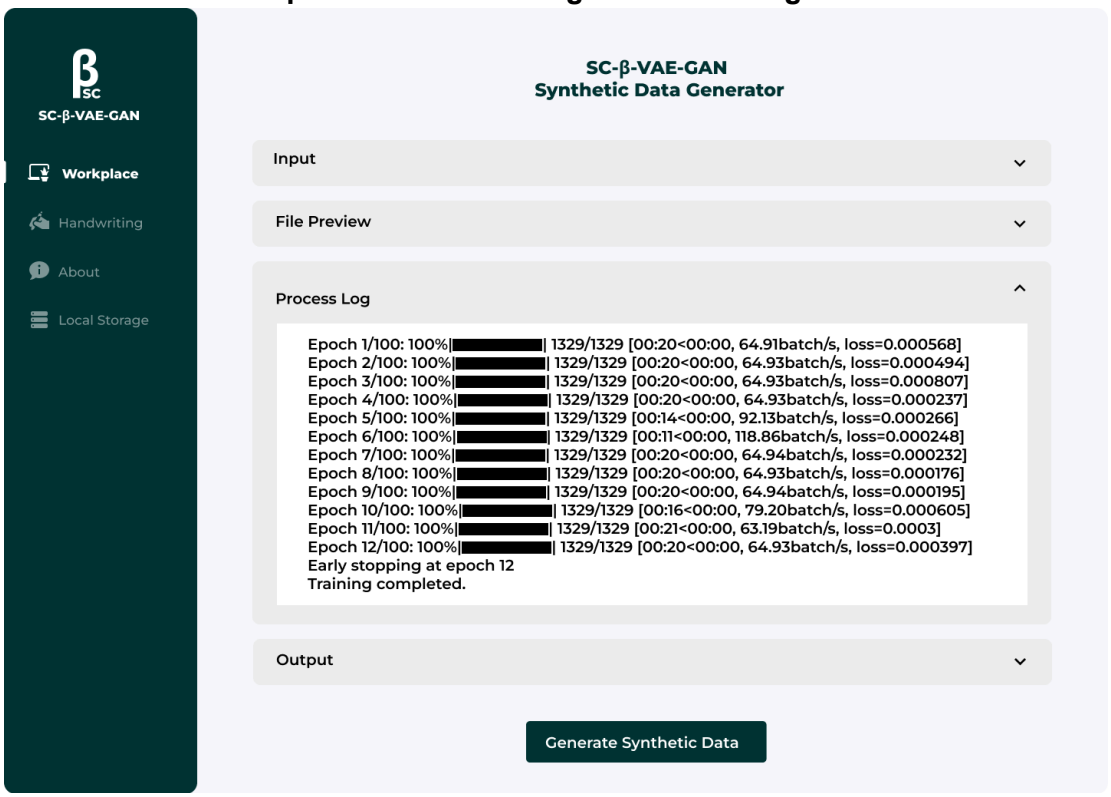
SC-β-VAE-GAN Main Page - Input Section



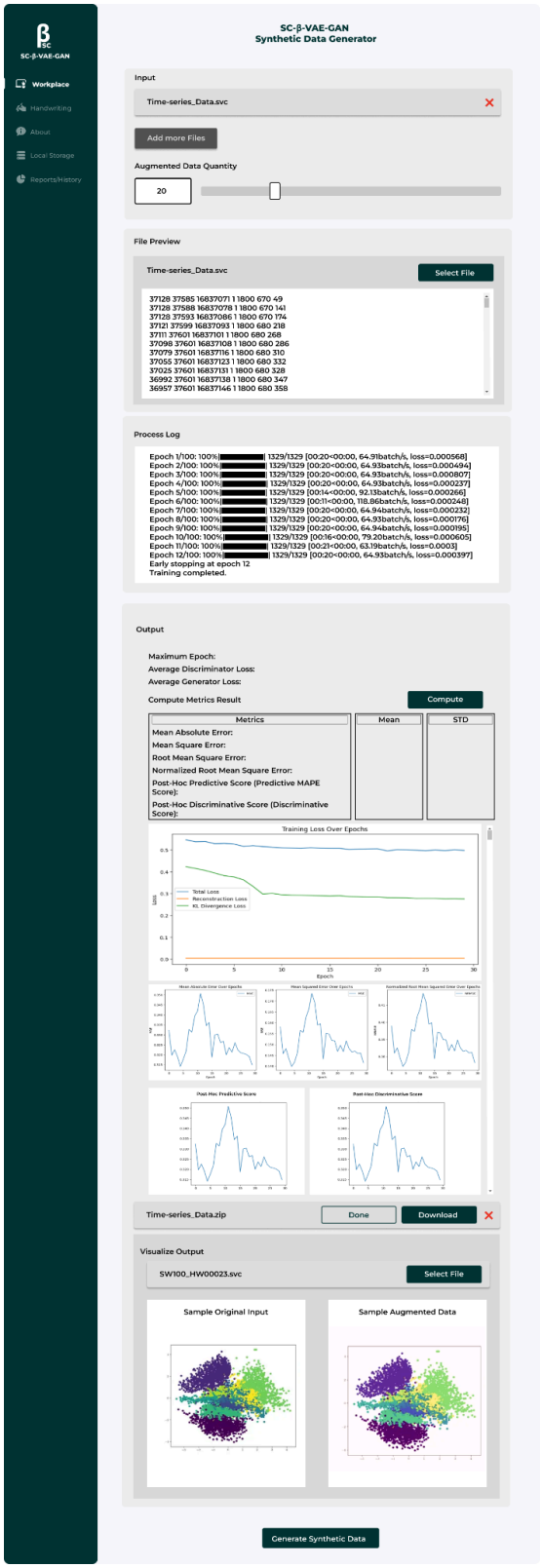
SC-β-VAE-GAN Main Page - File Preview Section



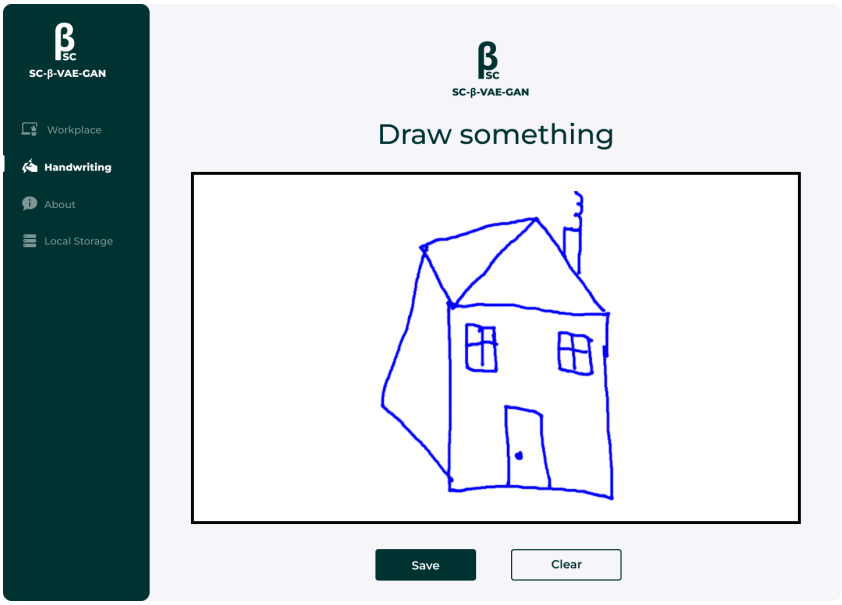
SC-β-VAE-GAN Main Page - Process Log Section



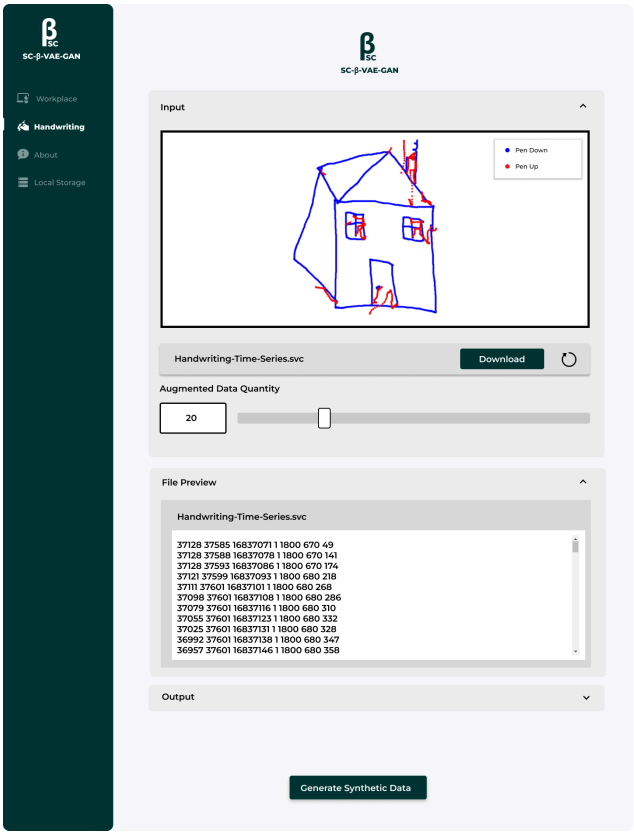
SC-β-VAE-GAN Main Page - Output Section



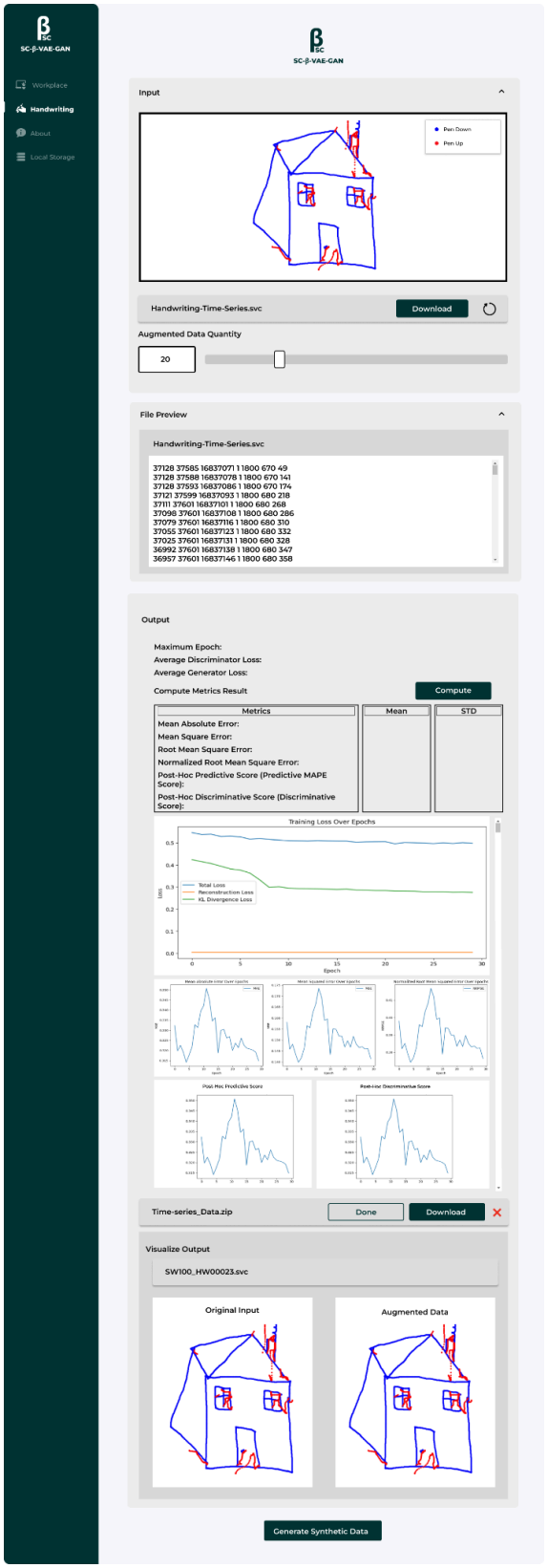
SC-β-VAE-GAN Handwriting Page - Handwriting Section



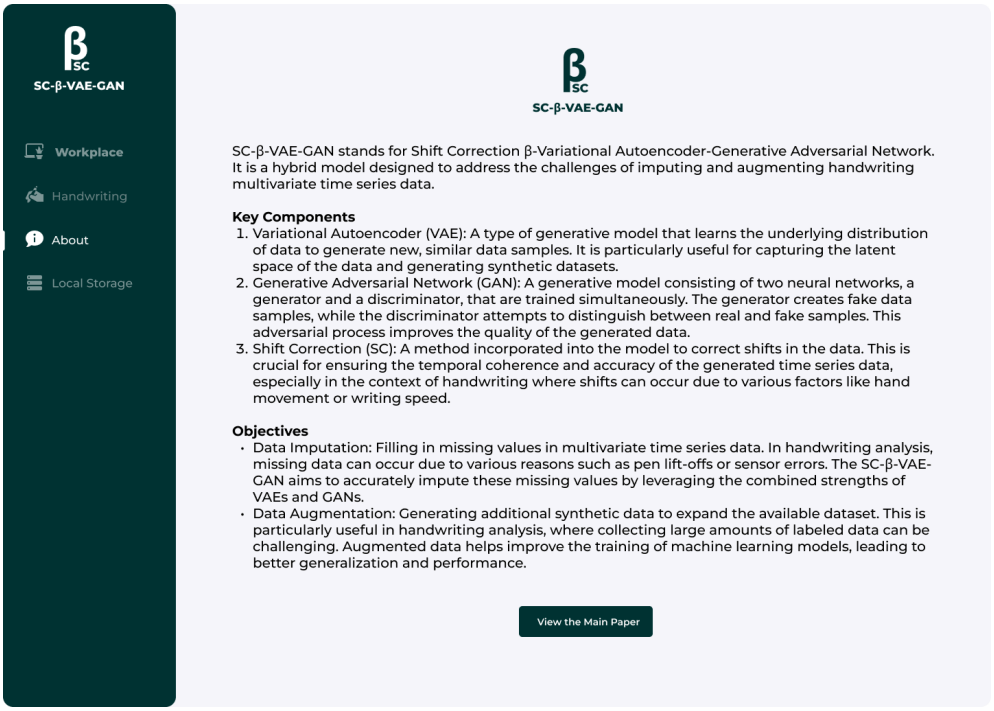
SC-β-VAE-GAN Handwriting Page - Handwriting Preview Section



SC-β-VAE-GAN Handwriting Page - Output Section



SC-β-VAE-GAN About Page



SC-β-VAE-GAN Local Storage