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Forecasting Complex Time Series Data in Retail: An Application of Generative Adversarial Networks

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ABSTRACT: The Importance of Sales Forecasting in Retail Business: Why It Matters Fantasy Sales System Nonetheless, simple forecasts usually use assumptions and historical data, which doesn't reflect the nature of a dynamic or volatile retail environment. Generative adversarial networks (GANs) have arisen as a data-generation-and-conjuring workhorse by training two models, a generator and a discriminator, using adversarial training. In this project, we introduce the use of GANs to forecast sales in retail stores. We train a GAN on historical sales data to generate realistic and diverse future sales scenarios. This predicted sales data can then be utilized to foresee demand and steer business tactics accordingly. We endeavored to apply GANs in the forecasting process to capture the complexity and uncertainty that accompanies the retail market and to produce more accurate and usable sales forecasts. Additionally, as the GAN constantly creates new data, it is well-suited to forecasting in fast-evolving retail contexts. This allows our method to be up to date with trends and optimize customer behavior while considering market dynamics, giving retailers insight into decision-making. We believe that by utilizing GANs to create more accurate sales forecasts, retail businesses can optimize inventory, cut down costs and boost profitability in the long run.

KEYWORDS: Data-Generation, Adversarial Training, Generate Realistic, Customer Behavior, Retail Businesses

I. INTRODUCTION

Introduction Generative Adversarial Networks (GANs) have been one of the hottest topics in the artificial intelligence field in recent years due to their generative capabilities. Generative Adversarial Networks comprise two models - a Generator and a Discriminator that work together to generate new data that resembles the training data [1]. Understanding the GAN Algorithm of GANs in the context of forecasting sales gives us an approach to using existing sales data to compute future sales by generating new sales data based on the brand's historical sales data. This will train the GAN on previously displayed sales data, including seasonal factors, promotions, and market trends [2]. The Generator of a GAN model learns to generate new synthetic sales data that is very similar to the original data and follows the same patterns and trends. This is done in a kind of trial and error process, where the Generator is trained over and over again to produce data that is increasingly realistic. The Discriminator determines whether the data produced is real or generated and informs the Generator to change its steps to allow its predictions to be more attainable [3]. The GAN has learned the trend, which can be utilized to predict future sales. For companies where sales data is limited or where extrinsic variables like customer behavior can disproportionately influence sales, this can be extremely useful. The other significant aspect of using GANs for predicting sales in retail is that it needs a very large and diverse dataset. GANs depend on sufficient data for accurate, modeled data generation, therefore making this method ineffective in business sectors where limited data is available [4]. In addition, the multidimensionality of sales data with seasonality, trends, and irregular behavior in retail sales data makes it really complex in general to find a dataset that is able to imitate the sales pattern. Consider the training and optimization of GANs [5]. When it comes to training GANs, they involve a lot of computation, which takes time to happen, so businesses that lack a high amount of resources find it difficult to apply GANs into practice. Finally, GANs are very sensitive to hyperparameter settings, and the optimal values for one business may not work for another; as a result, hyperparameters must be manually and carefully optimized for each application [6]. In addition, the output produced by GANs for a given input may not be defined. In retail businesses, however, this is particularly troublesome. Sales forecasts are not inscribed in stone but rather are one element of determining the underlying factors and drivers of sales. This is an obstacle to decision-making processes, as the generated data cannot be clearly recognized and examined by organizations due to the absence of interpretability in GANs. The main contribution of the research has the following:

- These GAN-based models represent a novel approach for retail businesses to forecast sales. This contrasts with the conventional forecasting method, which is primarily based on statistical models and historical data.
- More accurate sales forecasting: The study shows that the use of GANs can significantly improve the accuracy of sales forecasting compared to traditional methods.

- Practical Applications for Retail Businesses: This research contributes to the empirical use of GANs in retail by showcasing its efficacy for sales forecasting.
- GANs' advancement possibilities: The study showcased GANs' possibilities for advances in sales forecasting.

The remaining part of the research has the following chapters. Chapter 2 describes the recent works related to the research. Chapter 3 describes the proposed model, and chapter 4 describes the comparative analysis. Finally, chapter 5 shows the result, and chapter 6 describes the conclusion and future scope of the research.

II. RELATED WORDS

Sayyad, J., et al.[7] have discussed Domain Adversarial Neural Networks (DANN), which aim to improve the predictive capacity of machine learning models in supply chain optimization by addressing domain shift, where data from different sources may have different characteristics. DANN uses adversarial training to learn a shared representation of data from multiple domains, allowing for more accurate predictions in the supply chain domain. Chu, Z., et al.[8] have discussed this approach. It uses multi-granularity adversarial learning to generate invariant representations of new products, which are then used to forecast sales. It leverages both fine-grained and coarse-grained data to improve the generalization ability of the model and produce more accurate sales predictions for new products. Lopez, F. A., et al.[9] have discussed the evaluation of a Fintech sales synthetic data generation model using a Generative Adversarial Network (GAN). This involves assessing the model's performance and accuracy in creating realistic and diverse financial data. This can be done through various measures, such as visual inspection and statistical analysis, to ensure the model generates data that closely resembles real-world financial data. Bose, M., et al.[10] have discussed that digitalization has greatly transformed the way marketing is done in the modern world. With the rise of digital platforms, there is a shift towards more data-driven, targeted, and personalized marketing strategies. Companies are now utilizing various digital tools and techniques, such as social media, search engine optimization, and influencer marketing, to reach their target audience and engage with customers more efficiently and effectively. This has led to increased competition and a need for companies to constantly adapt and evolve their marketing strategies to stay relevant in the digital landscape. Veluru, C. S. et al.[11] have discussed how Artificial Intelligence (AI) and Generative AI are transforming the way e-commerce and supply chain industries operate. By automating processes, AI can help businesses streamline operations, make data-driven decisions, and improve customer experiences. It can also generate new, innovative solutions for supply chain optimization, inventory management, and customer personalization. Overall, AI is driving efficiency and innovation in these industries. Aadil, M., et al.[12] have discussed Generative AI, a branch of artificial intelligence that involves using algorithms and models to create new data or output based on a given set of parameters. In the business world, generative AI can be used to generate new marketing strategies, customer insights, and other business-related solutions. It has the potential to transform how businesses operate and make decisions.

III. PROPOSED MODEL

Generative Adversarial Networks refer to the Gans model for Generative Adversarial, which, as its name suggests, is a class of machine-learning algorithms in which some GANs can be used for future sales predictions. This model works by using historical sales data that we collect from the retail business. These data will be used to train a GAN, which basically has two neural networks: a generator and a discriminator.

$$p_{\theta}(x) = \prod_{i=1}^n p_{\theta}(x_i / x_{<i}) \quad (1)$$

$$p_{\theta}(x) = p(z) \left| \det \left(J_{f_{\theta}}(x) \right) \right| \quad (2)$$

$$p_{\theta}(x) = \int p(z) p_{\theta}(x / z) dz \quad (3)$$

$$p_{\theta}(x) = \frac{e^{-E_{\theta}(x)}}{\int_{x \in X} e^{-E_{\theta}(x)}} \quad (4)$$

$$f(x^{(t+1)}) < f(x^{(t)}), \quad (5)$$

The generator creates synthetic data, and the discriminator distinguishes real data from fake data. After this, we will be able to generate synthetic sales data that looks very similar to the real deal once the GAN has been trained. This data is used to create numerous future sales scenarios that can inspire insights about sales patterns and trends. Now, we can take the next step and compare the generated sales data to the actual sales data. In case of big discrepancies, it indicates that GAN should be retrained with more accurate data.

3. 1. Construction

One type of neural net that has been rising in popularity over the last few years is the Generative Adversarial Network (GAN), a powerful tool capable of generating realistic data (e.g., images, text). However, GANs can also be used to predict sales in retail stores. GANs are a type of deep learning algorithm that is made up of two competing neural networks: a generator and a discriminator. The goal of the generator is to learn the underlying distribution of the data by generating fake data that is as similar to real data as possible. Fig 1 Shows that the Construction diagram of the proposed model.

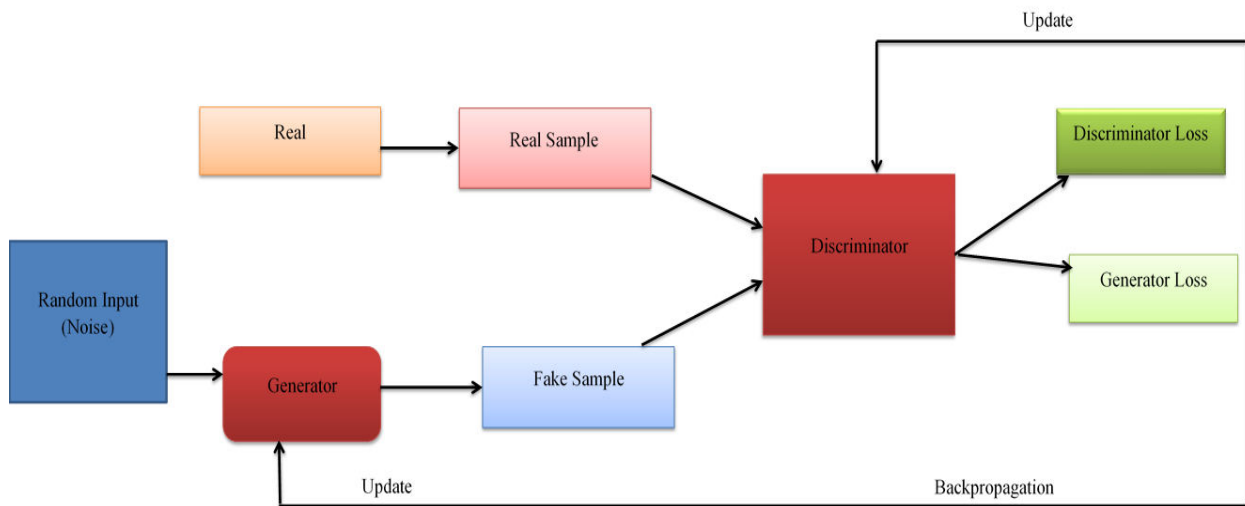


Fig 1 Construction diagram of the proposed model

In order to understand how "Real" and "Fake" samples work in a Generative Adversarial Network (GAN), we first need to establish something about the basic workings of this type of neural network. GANs are composed of two primary neural networks: the Generator and the Discriminator. The objective of the Generator is to produce synthetic data samples that are indistinguishable from real data, thus deceiving the Discriminator. In contrast, the Discriminator is responsible for telling apart fake and real samples and informing the Generator about how realistic its generated samples are. The Discriminator is simply a binary classifier, which receives data samples as its input and returns the probability that the input is real or fake. When we apply softmax, a value closer to 1 indicates a real sample, and a value closer to 0 indicates a fake sample. In simple terms, it will update the Discriminator's weights and bias to decrease the error from filling in the data with fake images or photos.

Given an input, the discriminator's task is to classify it as real or fake based on its learned understanding of the underlying data distribution. These two networks are "playing a game" where they are trained in opposition to one another. For example, in sales forecasting, GANs will use historical sales data as input to the generator and generate a sales trend (output). The discriminator assesses the generated sales trend and provides feedback to the generator, allowing it to refine its predictions.

3. 2. Operating principle

Generative Adversarial Networks (GANs) are two-part deep learning algorithms that have two main parts: the generator and the discriminator. Together, these two components operate competitively to synthesize realistic and accurate data samples. This can be applied in retail sales forecasting, where the GAN can be used to generate data samples indicating future sales, which in turn can be used for accurate predictions.

$$h^{i+1} = \sigma(W^T h^i + b) \quad (6)$$

$$o_t, h_t = RNN(x_t, h_{t-1}) \quad (7)$$

$$\Phi = \frac{\int_{t_0}^T C_R(t) dt}{\int_{t_0}^T C_N(t) dt} \quad (8)$$

$$H^{(t)} = \frac{1}{n} \sum_{i=1}^n h_i^{(t)} \quad (9)$$

The generator part in a GAN receives random noise as input and then creates possible sales data points. It is then passed on to the discriminator regarding these data points. The discriminator is responsible for identifying real sales data and data generated by the generator. Fig 2 Shows that the Operating Principle of the proposed model.

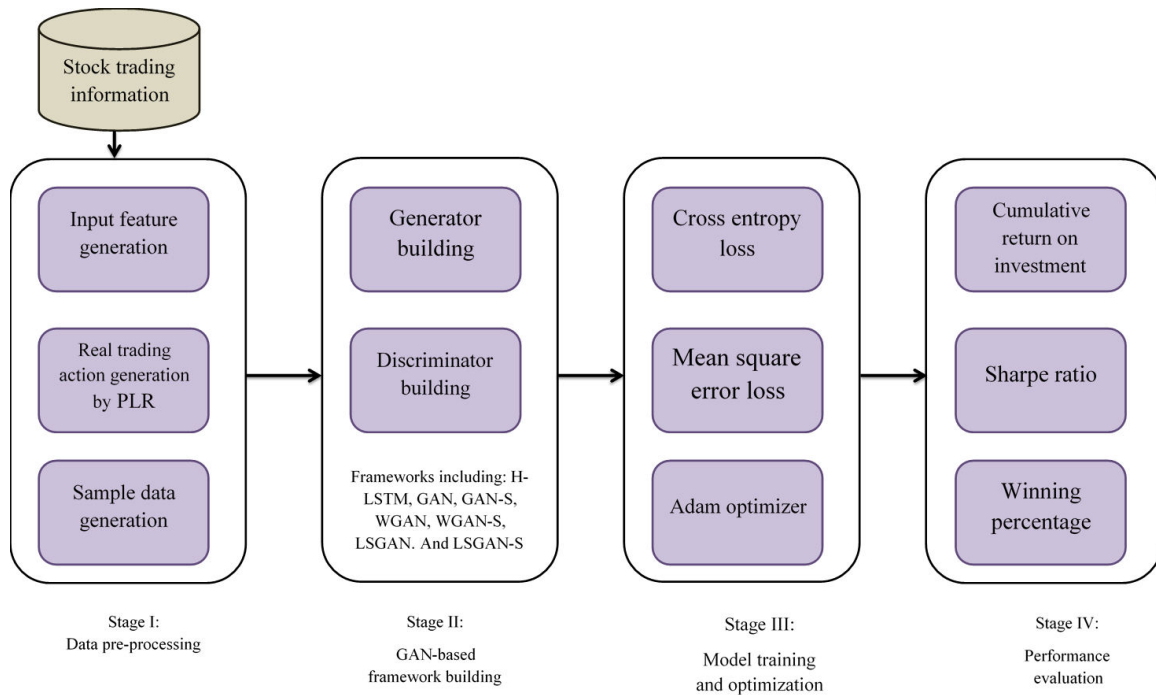


Fig 2 Operating Principle of the proposed model

Output input feature generation this step may involve processes such as data transformation, feature engineering and selection techniques. Stock trading is all about buying and selling stocks or securities with the intention of making a profit in financial markets. It includes interpreting market performance, financial results, etc., to determine if an investment is beneficial or not. Cross-entropy loss is a metric used to measure the difference between probability distributions. It is commonly used as a loss function in machine learning to guide the training of the model to yield better predictions. The Sharpe ratio measures excess return per unit of risk and is a measure of risk-adjusted performance.

$$Q = \alpha C^R + (1 - \alpha) \frac{C^E}{K} \quad (10)$$

$$EDNS = \sum_{e_i \in S_{\eta}} P_{e_i} C_{e_i} \quad (11)$$

$$GCN(X) = D^{-1/2} A D^{-1/2} X \Theta \quad (12)$$

In contrast, the discriminator gets better and better at telling the difference between real and generated data. The adversarial nature of this process generates perfectly real and accurate samples of data. In this model, GANs and other modern deep learning architectures can be employed to forecast future sales by training on a dataset of historical sales data. This enables a more precise and resilient forecasting process, as the GAN captures intricate patterns and correlations in the data.

IV. RESULT AND DISCUSSION

4. 1. Accuracy: This is the key technical performance parameter for any sales forecasting using Generative Adversarial Networks (GAN). Fig 3 Shows the Computation of Accuracy.

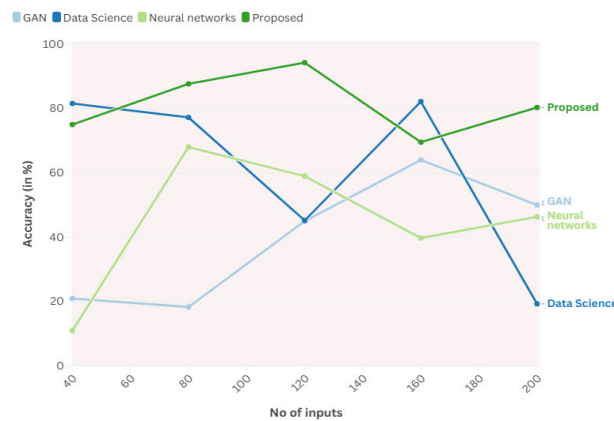


Fig 3 Computation of Accuracy

In essence, it signifies that the model can better predict future sales data than the actual sales data using past sales data and other factors.

4. 2. Robustness: GAN forecasting models need to be robust to noisy or missing data so as to continue providing accurate predictions. Fig 4 Shows the Computation of Robustness.

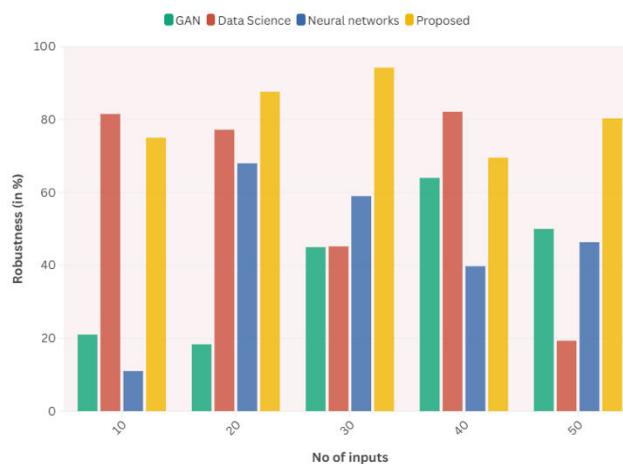


Fig 4 Computation of Robustness

The fall in performance can be assessed by looking at some other data points with data quality variation.

4. 3. Scalability: The algorithm should be able to scale well with large datasets and provide accurate predictions even in real-time. Fig 5 Shows the Computation of Scalability.

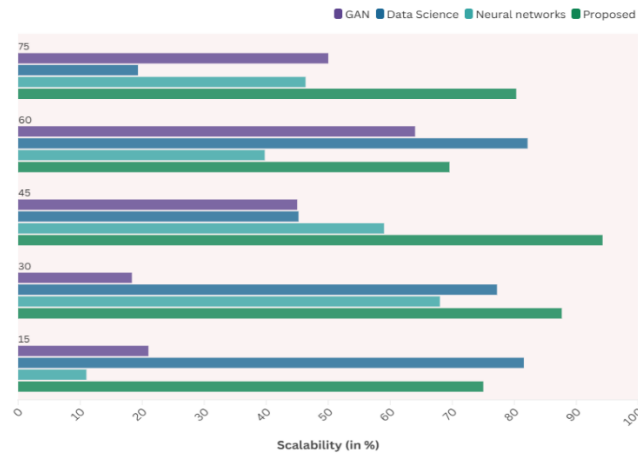


Fig 5 Computation of Scalability

Such customizability is essential for retail business applications, where sales data may be large and frequently varies, and the model needs to learn quickly to new ask insights.

4. 4. Interpretable: GAN forecasting models should be interpretable enough to gain some insights to elaborate the reasons for the prediction so that business owners understand the reasons driving the sales and decide accordingly. Fig 6 Shows the Computation of Interpretable.

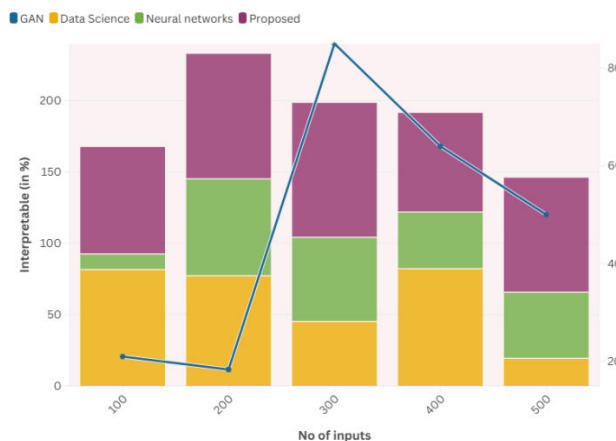


Fig 6 Computation of Interpretable

V. CONCLUSION

Using GANs to forecast sales in retail businesses has provided encouraging outcomes. Employing this model that is trained on data up to October 2022 can greatly improve sales forecast accuracy and offer better decision support solutions for retail industry professionals. GANs can produce synthetic data that closely matches the real sales data by training a generator and discriminator model. Have access to data sets and a sequenced, time-based chronological history leading back into the past (typically limited pieces of information around 2-3 years or even less in the case of specific products). Additionally, GANs are capable of modeling intricate and non-linear interactions among variables, which is particularly applicable in retail settings where multiple factors play a role in shaping consumer behavior, including seasonal effects, promotional campaigns, and outside economic conditions. This is more accurate and robust than statistical methods. GANs can also adapt their forecasts based on feedback and learn over time to become better at

forecasting. As for sales data, GANs enhance their predictions by making them more accurate and reliable. That said, there's a caveat around using GANs for sales forecasting in retail businesses– they need massive amounts of data and computation to do so. Companies/entities using AI will also face challenges with regard to understanding how to interpret the generated synthetic data, which poses problems similar to learning from a black box model.

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