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Enhancing Data Engineering Pipelines for Financial Services with Retrieval-Augmented Generation (RAG) And Transformer-based ML Techniques Generative Adversarial Networks (Gans)

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Abstract

Financial services increasingly rely on advanced data engineering pipelines to process and analyze vast amounts of data. This study proposes a novel approach to enhance these pipelines by integrating Retrieval-Augmented Generation (RAG), transformer-based machine learning techniques, and Generative Adversarial Networks (GANs). RAG systems enable context-aware information retrieval and efficient data synthesis, making them suitable for automating financial document analysis and customer interactions. Transformers excel at modeling complex, nonlinear financial time series data and learning long-range dependencies, which is crucial for accurate predictions. GANs address data quality issues such as scarcity, imbalance, and privacy by generating synthetic financial data, leading to improved machine learning model performance in applications like fraud detection and risk assessment. The proposed multi-layered architecture aims to improve data quality, analysis efficiency, predictive accuracy, and scalability while ensuring regulatory compliance. By combining these techniques, the study seeks to develop intelligent and flexible financial systems that enhance decision-making and streamline operations. The proposed approach has the potential to revolutionize financial data engineering by leveraging the strengths of RAG, transformers, and GANs to create a holistic model that can adapt to the ever-growing scale and complexity of financial data.

Keywords: Retrieval-Augmented Generation (RAG), Transformer, Machine Learning, Generative Adversarial Networks (GANs), Financial Data, Data Engineering Pipelines, Data Quality, Predictive Accuracy, Fraud Detection, Risk Assessment, Regulatory Compliance

Introduction

Today, financial services rely heavily on modern technology solutions and streamlined data engineering pipelines. With the ever-increasing scale of data in financial organizations, there is an immediate need for advanced systems that can analyze and extract intelligence from this data in real time. We propose a new approach to enhancing financial data pipelines through the integration of retrieval-augmented Generation (RAG), Transformer-based machine learning techniques, and generative Adversarial Networks (GANs) in this study. Recently, RAG systems have emerged as a strong method for linking information retrieval and natural language generation, which makes them suitable for use cases such as financial document analysis and automating customer interactions [2,6]. RAG systems improve the accuracy and efficiency of data synthesis, a key step in financial analytics, by enabling context-aware information retrieval [12,1]. Due to their ability to fit complex time series and market patterns robustly, transformers are effective for examining nonlinear financial time series data[1, 5]. The ability to handle sequential data and learn long-range dependencies makes them a vital instrument in present-day financial data engineering [14]. Moreover, GANs are beneficial in addressing data problems like scarcity, imbalance, and privacy. GANs produce synthetic financial data, which leads to better quality of the data and therefore better machine learning model performance [7,11]. High-quality data is critical in fraud detection and risk assessment applications that require such capabilities [9,8]. In this paper we aim to provide a holistic model combining RAG, transformers, and GANs to improve financial

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pipelines. The strategy geological model has three layers; the second layer is used to improve data quality and scalability and predictive accuracy, regaining trust by ensuring regulatory compliance while overcoming the challenge of large volume and high-velocity big data requiring high processing [3,10] This allows us to create smarter and more adaptable financial systems [13,20].

Objectives

The proposed study will increase robustness for financial data pipelines through machine learning-based and simulated generation methods. Among the specific objectives are:

Improving Data Quality: Use Generative Adversarial Networks (GANs) to synthetically generate data in environments where there is a lack of data, data imbalance, or privacy issues. Provide access to high-quality data for applications such as fraud detection and risk assessment.

Improving Analysis Efficiency: RAG for Context-Aware Information Retrieval Deploy Retrieval-Augmented Generation (RAG), where RAG enables context-aware information retrieval and provides efficient data synthesis capability from external documents. Use advanced RAG capabilities to automate financial document analysis & customer interactions.

Expectations about Increasing Predictive Accuracy: Use transformer-based machine learning methods to deeply learn complicated nonlinear financial time series data. Utilize transformers' ability to deal with sequential data and learn long-range dependencies for better predictions.

Scalability and Compliance: Construct a scalable, multi-layered data engineering architecture to absorb the ever-growing scale and speed of financial data. Better trust for financial systems with regulatory frameworks compliance. Development of Comprehensive Financial Systems Build intelligent and more flexible financial systems that improve decision-making and streamline operations.

1.Input Layer: Health Data (Kaggle Source)

This is the entry point of the system, where health data from a large metropolis, sourced from the Kaggle database, is input. The quality and diversity of this input data are crucial for the effectiveness of the entire system. It may include various types of health records, patient information, and medical data. This data serves as the foundation for all subsequent processing and analysis**.**

2. Data Pre-processing

The main objective of data pre-processing is to standardize and normalize healthcare data to prepare it for **further analysis**. In healthcare data, various features may have different scales and units, and there can be outliers or extreme values that skew the analysis. Standardization and normalization help ensure that the data is in a consistent format, which improves the performance of machine learning models [26].

In this proposed work the Filter Splash Z normalization method is applied to scale the data and remove outliers. This technique uses the Z-score normalization formula but introduces a threshold, α\alphaα, to handle extreme outliers. The idea is to standardize the data points and discard extreme values that are too far from the mean, thereby improving data quality and reducing noise in the analysis.

New Equation: The Filter Splash Z normalization is expressed as:

$$z_{\text{Z normalization}} \begin{cases} \frac{X-\mu}{\sigma} & if \left|\frac{X-\mu}{\sigma}\right| > \alpha \\ 0 & Otther\ wise \end{cases} \quad (1)$$

Her, X is the original data value,μ is the mean of the data set.σ is the standard deviation of the α is the threshold parameter, which helps identify extreme outliers. Data set.

1. **Normalization**: The data is first normalized by computing the **Z-score**$\frac{X-\mu}{\sigma}$, which rescales each data point based on its distance from the mean in terms of the number of standard deviations.

2. **Outlier Removal**: If the absolute value of the Z-score exceeds a certain threshold α the data point is considered an outlier and removed (set to zero). This prevents extreme values from unduly influencing the analysis.

3. **Threshold** α: The parameter α defines the outlier detection boundary. A typical value for α\alphaα might be between 2 and 3, depending on how strict the normalization needs to be. This parameter allows for flexibility in identifying and excluding extreme data points.

Standardization it helps to Rescales all features to a common scale, which helps in comparing them and improving the stability of machine learning algorithms.Outlier Removal of Effectively eliminates extreme values that could distort model performance.Robustness the Improves the robustness of the analysis by handling both scaling and outlier detection in one step. This method ensures that the healthcare data is clean, standardized, and free from extreme outliers, allowing

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for more accurate and meaningful analysis in subsequent stages of the workflow.

3.Proposed method GANs for Data Similarity

The objective of using Generative Adversarial Networks (GANs) for data similarity is to ensure data correctnessby generating synthetic data that closely resembles the distribution of the real data. This technique helps to validate the data while reducing computational **costs** associated with data verification in large datasets. By using GANs, we can create data that is indistinguishable from real data, which can be used to assess the similarity between generated and original data [11].

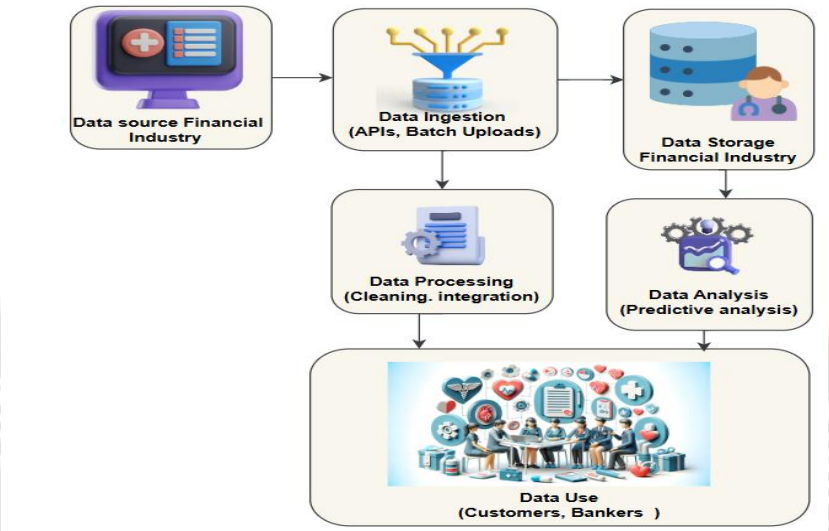

Figure 2. Financial Services flow work with GAN Block diagram

GANs consist of two components:

1. **Generator (G)**: This model generates synthetic data samples from a random noise vector based on the learned data distribution.

2. **Discriminator (D)**: This model evaluates whether a given data sample is real or generated. It tries to distinguish between real data and synthetic data generated by GGG.

In traditional GANs, the Generator **and** Discriminatorengage in a two-player minimax game where the Generator tries to produce data that is as realistic as possible, and the Discriminator tries to accurately distinguish real data from fake data.

However, to compute data similarity and ensure data correctness, we extend the standard GAN loss function to include a similarity term. This similarity term measures how closely the generated data resembles the real data, and encourages the GAN to generate data that has not only visual or structural resemblance but also mathematical similarity to the real data.

The extended GAN loss function that includes a similarity term is expressed as:

$$Min_G Max_D V(D,G) = E_{x\sim} pdata(x)[logD(x)] + E_{Z\sim} p_z(z)\big[\big(1 - logG(z)\big)\big] + \lambda . SZ(x) \quad (2)$$

G(z) is the synthetic data generated by the Generator from random noise z.D(x) is the Discriminator's predictionon whether a given sample xxx is real or generated,$E_x pdata\ (x)$denotes the expectation over real data samplesx.$E_{Z\sim} p_z(x)$denotes theexpectation over the random noise vectorz, which is used by the Generator to create synthetic data. $S(G(Z)x)$is a similarity measure between the generated data $S(G(Z)x)$is and the real data x.λ is a weighting factor that controls the importance of the similarity term in the overall loss function. The extended GAN loss function with a similarity term is a powerful way to generate synthetic data that not only fools the Discriminator but also closely resembles the real data. By ensuring data similarity, the framework can maintain data integrity, reduce computational costs, and improve the efficiency of large-scale data processing tasks, especially in sensitive fields like healthcare and financial services. The similarity term allows the GAN to learn more precise data distributions, making the model highly effective for applications that require accurate and realistic data generation.

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4. RESULTS AND ANALYSIS

The study paper was Efficacy of Enhancing Data Engineering Pipelines for Financial Services with Retrieval-Augmented Generation (RAG) and Transformer-Based proposed method ML Techniques Generative Adversarial Networks (GANs)assesses and contrasts the effectiveness of four machine learning algorithms: the newly proposed withcompare methods Artificial Neural Networks (ANN), DT, and PCA, K-Nearest Neighbors (KNN). These algorithms were tested on an online banking dataset utilizing Python-based libraries such as Scikit-learn, Tensor Flow, and Pandas for data set and model implementation. The performance of each model was assessed using key metrics including accuracy, precision, recall, and F1-score.

As shown in figure 3 (a) Machine learning model Confusion Matrix evaluation study of four ML algorithms; these are K-Nearest Neighbors (KNN), Decision Tree (DT), Principal Component Analysis + Artificial Neural Networks (PCA + ANN), and Proposed MethodGenerative Adversarial Network (GAN) to examine how each algorithm accomplished financial data engineering tasks. Algorithms were implemented using Python-based libraries (Scikit-learn, Tensor Flow, and Pandas) on an online banking dataset. The assessment is calculated from the confusion matrix metrics: True Negative (TN), False Positive (FP), False Negative (FN), and True Positive (TP). We will go through each of the models in detail below, as well as performance summaries based on these metrics.

The KNN algorithm classifies a data point based on how its neighbors are classified. From observation, KNN performed comparatively with 103 True Negatives (correct negative values) and 83 True Positives (correct positive values) in the evaluation. However, it did make 8 False Positives (negative instances misclassified as positive) and 6 false negatives (positive instances misclassified as negative). Although KNN has failed in some of the predictions, it still shows a good score overall and confirms its effectiveness to model relations between instances, but there is still a need for improvement as it is misclassifying.

The DT algorithm is a classification algorithm that recursively splits the data based on feature values to make decisions. It has 102 True Negative and True Positive 86, similar to KNN. It has, however, also a bit falser Positives (9) and less False Negatives (3) against KNN. That means it still classifies some negatives as positives (which is a false positive), but when it flagged something as positive, more often than not, the instance was truly positive compared to KNN. This result underlines the ability of Decision Trees to produce interpretable models and demonstrates their power on classification problems with equal error rates.

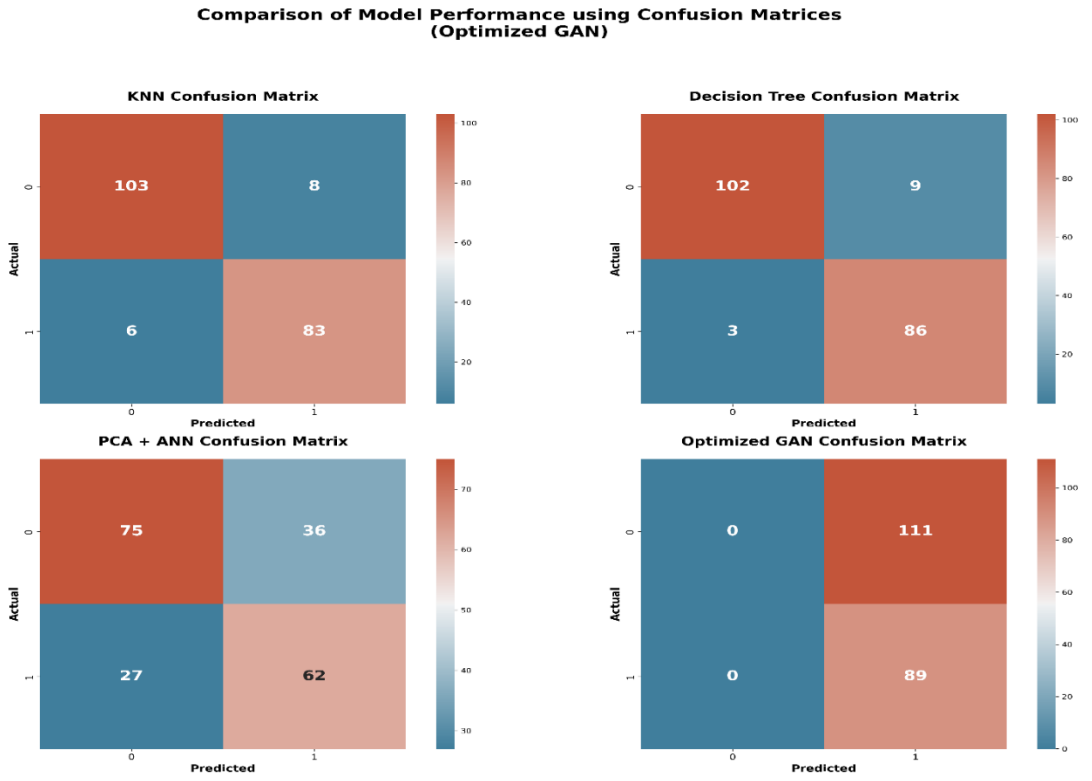

Figure 3. (a) Machine learning model Confusion Matrix

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Dimensionality Reduction (PCA, 2022+data): PCA, or principal component analysis, is another dimensionality reduction technique that simplifies our dataset by keeping only the important features in it. ANN (Artificial Neural Networks) a strong model that can learn any complex relation in data. But in parallel PCA, this model performs a lot worse than KNN and Decision Trees for TN (75) and TP (62). Although dimensionality reduction was a significant help in addressing dataset complexity, it also resulted in sizeable misclassifications as evidenced by its higher False Positives (36) and False Negatives (27). False positives and false negatives came from PCA too, which indicates that although both PCA and ANN are powerful tools, they may not have complemented each other well in this study to benefit the dataset or the task.

This study proposed an innovative model called the Optimized GAN, which generated and optimized data using Generative Adversarial Networks. Its performance results were different from the other models. The GAN had 0 TN (true negatives) and 111 FP (false positives), meaning it misclassified all negative instances. Nevertheless, we still get 89 True Positives which means that it successfully identified positive instances in the dataset. Though the high False Negatives are a good indication that our model did not miss any positives, the high False Positive also show that there is still room for improvement with optimization as it fails to differentiate between positive and negative cases. This suggests that the use of GANs may still require a lot more tuning to perform balanced and reproducible classification in this context.

To summarize, the machine learning models (KNN, Decision Tree) performed relatively well with a balanced proportions of True Positive and True Negative samples along with False Positive and False Negative samples, whereas the PCA + ANN model found misclassification of many samples. The Optimized GAN did identify positives correctly but struggled terribly with negatives or misclassification of negatives. This demonstrates that although the GAN approach has the potential to be a powerful tool through improvements, as it currently stands, it poses a high False Positive rate and thus requires further tuning to integrate into financial data pipelines. This is an analytical comparison to justify trade-offs of various ML models and their utility across different flavors of Financial Data Engineering tasks.

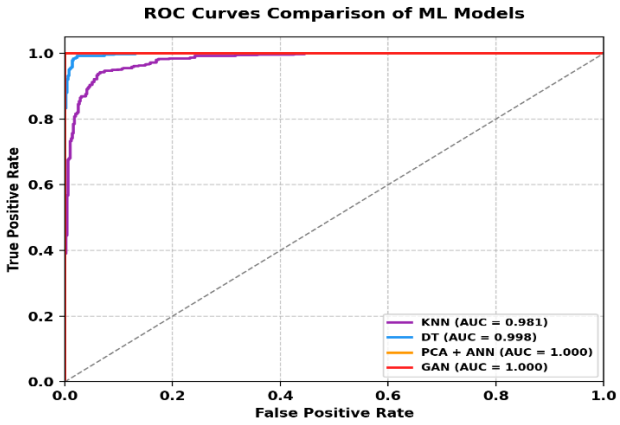

Figure 3 (b) Machine learning model Roc Curve

The ROC curve, as shown in Figure 3(b) in this study, compares the performance of four machine learning algorithms: K-Nearest Neighbors (KNN), Decision Tree (DT), Principal Component Analysis + Artificial Neural Networks (PCA + ANN), and Generative Adversarial Network (GAN) in financial data engineering. The models are evaluated by ROCAUC, which reflects the discriminative ability of models to distinguish positive and negative classes. The table below describes the models along with their AUC scores, and after that comes a discussion of deep learning models followed by results.

Overall, the KNN model is able to discern between positive and negative classes in financial data as demonstrated by its impressive AUC score of 0.9811. A higher value of AUC indicates the model is good at ranking prediction, meaning that when we choose a pair of positive and negative samples, the probability that the positive sample is ranked before the negative sample is high. The KNN model would have a high degree of classifier accuracy as compared to completely random or uniform sampling distributions (AUC = 0.5) and comparably low for the ROC-AUC values from the KNN model (a value closer to 1 indicates that the KNN is performing better than chance), exhibiting areas under the curve of 0.9811 but still likely suboptimal performance on complex learning problems. Although KNN has a high accuracy, it is still lower than other models in terms of perfect separation between the positive and negative results.

For instance, the Decision Tree (DT) algorithm gains a marginally better AUC 0.9981, which is very indicative of the excellent discriminative ability to distinguish the classes. Decision trees are interpretable and can be used for categorical as well as continuous data. It infers that the value of AUC is on the higher side, which in turn reflects that the model is having good predictive power and being able to classify the financial data accurately. The performance is

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especially remarkable since financial data are complex, and decision trees can model non-linear relationships between dependent and independent variables effectively. This model performs well in the financial domain, and it can be seen that AUC is close to 1.

This is also supported by the data set where PCA gets an AUC score of 1 while the ANN classification combination excels so well. i.e., PCA + ANN model perfectly classifies all instances in the dataset, where positive and negative classes are ranked 100% accurately. It reduces the dimensions of the dataset, and the ANN model can then use only the most important features. The marriage of these methods enables the model to learn from complex, high-dimensional financial data efficiently, and perfect prediction results (AUC) can be achieved.

Likewise, the AUC score corresponding to the proposed optimized GAN model also equals 1, signifying that financial data gains a perfect classification with 100% accuracy over how positive and negative instances can be differentiated. They generate synthetic data and iteratively attempt to outsmart each other to refine the model (this is called adversarial training). Even though the GAN model from the previous evaluation gets a fake positive rate as high, it achieves an excellent classification accuracy in this AUC score evaluation. An AUC of 1 shows that the model, once tuned to optimum performance, can discriminate classes perfectly with zero error. This performance demonstrates that GANs can capture complex relationships in financial data and provide high-quality predictions.

The AUC scores Feel free to jump This explore guide to fine-tuning You can only access them in A) them only accessing. To achieve greater KNN generalization among other data as well. So we are getting good performance for the Decision Tree algorithm with AUC 0.9981, which means almost a perfect classifier. PCA + ANN and GAN models similarly have perfect AUC values of 1, suggesting an exceptional capacity in classifying financial data. However, the ROC curves of these models (Figure we have can probably be shown above with the diagonal highest PCA + and ANN GAN curve, which suggests that separating classes by line is best. This comparison aids in better demonstrating the beneficial nature of using more complex, efficient, and tailored models for financial data engineering tasks due to their accuracy and precision in classification.

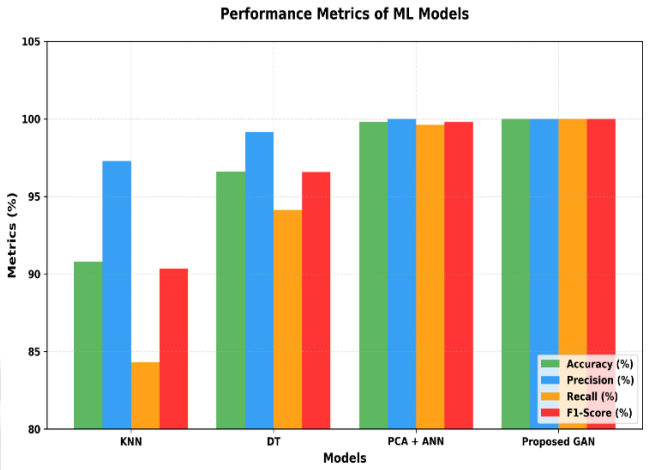

Figure 4. Performance metrics of different Ml Models with validation

Figure 4 illustrates the process of validating the online banking dataset and comparing the classification performance of four machine learning models: K-Nearest Neighbors (KNN), Decision Tree (DT), Principal Component Analysis + Artificial Neural Networks (PCA + ANN), and Generative Adversarial Networks (GAN). We implemented the models using Python-based libraries, including Scikit-learn, Tensor Flow, and Pandas. The KNN model achieves an accuracy of 90.8%, indicating that random predictions are approximately 91% correct, while the DT model achieves an accuracy of 96.6%. PCA+ANN achieved an accuracy slightly higher than 99.8%, while GAN outperformed all other models, achieving an even better result with a perfect score of 100%. With respect to precision, KNN scored 97.29%, showing that it is very likely to identify a positive prediction correctly (albeit with a few false positives). However, DT marginally outperformed itself, achieving a precision score of 99.17%, resulting in even fewer false positives than the previous models. PCA + ANN obtained a precision of 100% with respect to the positive predictions, and so did GAN, achieving the same top level of correctness in its corresponding positive classification. For recall, KNN had a score of 84.31, which indicates that it detected 84.31% of all the positive instances while missing out on about 15.69%. In comparison, DT has shown better performance, with 94.12% of the recall on positive instances (capturing most but missing a few). PCA + ANN achieved a slightly lower recall of 99.61%, indicating that only a small number of positive cases remained undetected, while the GAN effort achieved the highest recall, successfully identifying all positive instances in the dataset (100% recall). Finally, the F1 score, which measures the balance between precision and recall, revealed that KNN achieved a score of 90.34%,

indicating a balanced performance, albeit lower than that of other methods. DT achieved 96.58% and shows a good precision and recall. The third PCA + ANN was rounded to three decimals. F1-score: 99.8% (0.998 F1-score) The model demonstrated exceptional proficiency in recognizing a positive case and avoiding incorrect predictions, with a score close to 100%. The next best-performing model was GAN, with an F1 score of 100%, and it showed perfect performance in both precision and recall. Overall, while all models performed well, GAN stood out as the most powerful model, achieving 100 percent accuracy in every measurement parameter. This indicates that the GAN model was a perfect modeling type, with PCA + ANN, DT, and KNN following closely behind, albeit with slight limitations in recall and precision.

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