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Optimizing Financial Distress Prediction Models in Digital Startups Using Generative Adversarial Networks (GANs) for Financial Data Augmentation

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ABSTRACT

Digital startups are highly vulnerable to financial distress due to limited historical financial data and imbalanced datasets between healthy and distressed firms. These challenges reduce the accuracy of existing prediction models, hindering early risk detection for investors and policymakers. This study aims to optimize financial distress prediction in Indonesian digital startups by applying Generative Adversarial Networks (GANs) for financial data augmentation. GANs are used to generate synthetic financial data that replicate real-world distributions, particularly for the minority class, to balance the dataset. A quantitative experimental design was employed, comparing baseline and GAN-augmented models trained on financial ratios such as ROA, ROE, and DER. The results show that the GAN-augmented model achieved higher accuracy (92%), precision (91%), recall (88%), and F1-score (90%) compared to the baseline model. These findings confirm that GAN-based augmentation enhances model robustness and prediction reliability under limited data conditions. The study contributes to financial distress prediction literature by integrating deep learning with synthetic data generation, offering a practical tool for early detection of financial instability in digital startups and supporting data-driven risk management in Indonesia’s digital economy.

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INTRODUCTION

Indonesia has gained international attention for the remarkable growth of its digital startup ecosystem over the past decade. Supported by government innovation programs, venture capital investments, and an increasingly tech-savvy population, Indonesia has become one of the leading startup hubs in Southeast Asia. Data from StartupBlink said that Indonesia has 917 startups, representing 16% of all startups in South East Asia and this equals approximately 1 startup per 100,000 people, based on the latest data retrieved in 2025. Major cities such as Jakarta, Bandung, and Surabaya have evolved into innovation centers where thousands of digital startups emerge every year. The combination of a large domestic market, widespread internet access, and growing consumer adoption of digital services has created a fertile environment for technology-based entrepreneurship.

Despite this promising landscape, the sustainability of digital startups remains under significant threat. Behind the impressive growth figures lies a persistent issue, financial distress. Financial distress refers to a condition in which a company experiences difficulty in fulfilling its financial obligations, potentially leading to insolvency or bankruptcy (Aderin & Amede, 2022). This phenomenon is particularly critical in the startup context, where many firms prioritize aggressive growth and rely heavily on external funding sources such as venture capital and angel investment. High operational expenses, covering areas such as product development, marketing, and talent acquisition, often outpace revenue generation, leading to what is commonly known as a high burn rate. (Nurfauziyyah & Muslim, 2024) found that profitability, liquidity, leverage, sales growth, and firm size are the most studied variables related to financial distress. Consequently, startups are highly exposed to financial instability, especially when market conditions change or investor funding declines. In Indonesia, these vulnerabilities have been increasingly evident since 2021, when a number of digital startups began facing financial restructuring and operational cutbacks following shifts in investor sentiment and post-pandemic market adjustments. To illustrate this rapid development, data retrieved in 2025 from Startup Ranking shows a significant surge in the ecosystem, growing from approximately 992 startups in 2018 to over 3,180 active startups by early 2025. This underscores the importance of developing predictive models capable of identifying early signs of financial distress. (Silaban et al., 2024) emphasized that market fluctuations, funding difficulties, and weak financial management are key obstacles to early-stage startup sustainability.

Research on financial distress has been extensively conducted on established entities where data is abundant. (Kalbuana et al., 2022) examined the effects of profitability and governance on financial distress, focusing only on established LQ-45 companies, which typically possess comprehensive financial records. A systematic review by (Kuizinienė et al., 2022) found that key challenges in financial distress prediction include data imbalance and the need for complex models to capture multidimensional indicators. Furthermore, (Judijanto et al., 2024) found that standard logistic regression performs poorly on imbalanced data, while cost-sensitive or balanced machine learning algorithms improve prediction accuracy in these conventional corporate setting. However, these studies rely on the assumption that historical data is readily available and representative of long-term operations.

In contrast, research specifically targeting start-up companies presents a distinct novelty due to severe data limitations that render traditional approaches ineffective. Unlike public companies, startups operate as private entities with restricted access and short operational histories. For example, (Gunanto, 2023) analyzed 21 digital startups and obtained only 84 financial statement observations (2019–2022) after data cleaning. This scarcity creates a significant barrier. Moreover, the inherent class imbalance, where financially healthy startups outnumber distressed ones, creates model bias. Meanwhile, (Douzas et al., 2019) noted that SMOTE-generated data often lack realism and may cause overfitting by failing to capture original data complexity. Researched by (Ramadhanti et al., 2022) found that SMOTE and ADASYN each perform better depending on data distribution and the applied algorithm. Consequently, few studies have applied advanced augmentation methods like GANs to predict financial distress in Indonesian digital startups. This research aims to fill that gap by integrating GAN-based augmentation with deep learning models to enhance prediction robustness and reliability.

Recent developments in artificial intelligence (AI), particularly in deep learning, provide innovative solutions to these challenges. (Lau, 2021) showed that financial distress can be predicted using methods such as logistic regression, Altman Z-Score, Springate, Zmijewski, and Grover models. Deep learning models, such as Artificial Neural Networks (ANNs), are capable of identifying complex, non-linear relationships within financial data, offering superior predictive accuracy compared to conventional models. (Wayan & Ayuni, 2025), for instance, demonstrated that ANNs achieved 83.16% accuracy in predicting financial distress in Indonesia’s property sector, outperforming traditional Support Vector Machine (SVM) and PSO-SVM hybrid models. Researched by (D’Ercole & Me, 2025) used a CNN+GAN approach to predict global bankruptcies, achieving higher accuracy with synthetic data augmentation. (Li. Y et al., 2022) developed a hybrid XGBoost-MLP model for credit risk assessment in digital supply chain finance, outperforming single models. Meanwhile, (Prasetyo et al., 2023) showed that machine learning algorithms effectively classified Indonesian tech startups as “healthy” or “distressed” with promising accuracy. Nonetheless, deep learning models are highly data-dependent, limited and imbalanced datasets can cause overfitting and compromise generalization performance.

To address these issues, Generative Adversarial Networks (GANs) have emerged as a powerful data augmentation technique. Researched by (Motamed et al., 2021) showed that GAN-based data augmentation improved X-ray classification performance and reduced model bias in detecting pneumonia and COVID-19. (Kuntalp & Düzyel, 2024) developed GAN-based augmentation for widely separated cluster datasets, though not specific to startup financial data. GANs consist of two neural networks, the generator and the discriminator that work adversarial to produce synthetic data closely resembling real data. In financial distress prediction, GANs can generate realistic synthetic financial records, thus expand the dataset and balance the representation between distressed and non-distressed startups. This enables the predictive model to learn more comprehensive patterns and improve classification accuracy. Empirical studies have shown that GAN-based augmentation can enhance the robustness and reliability of financial prediction models, particularly when real-world data is scarce. (Silva et al., 2021) found that GAN-based data augmentation significantly improved financial distress prediction accuracy. (Zhang. J et al., 2022) also reported that GAN-based data enrichment enhanced deep learning models' early financial distress prediction accuracy. Meanwhile, (Nayak & Rout, 2024) designed a GAN-based hybrid model that improved corporate bankruptcy prediction compared to non-augmented models.

Therefore, this research aims to predict financial distress among Indonesian digital startups during the period 2021–2023 by integrating deep learning algorithms with data augmentation using GANs. The objective is to optimize the accuracy and reliability of financial distress prediction models in conditions of limited and imbalanced data, providing a methodological advancement that aligns with Indonesia's digital transformation agenda. The results are expected to contribute to both academic understanding and practical strategies for strengthening the financial resilience of digital startups in Indonesia's rapidly evolving innovation ecosystem.

METHODS

This study employs a quantitative approach using an applied experimental research design to develop and optimize a financial distress prediction model for digital startups in Indonesia. The experimental approach is chosen because it allows for testing and evaluating the impact of data augmentation techniques, specifically the use of Generative Adversarial Networks (GANs) on the predictive performance of a deep learning model. The overall research framework is illustrated in Figure 1, which outlines the sequential process from data collection and preprocessing to model training and evaluation. This flowchart represents the methodological flow of the study, emphasizing the integration of GAN-based data augmentation in the predictive modeling process.

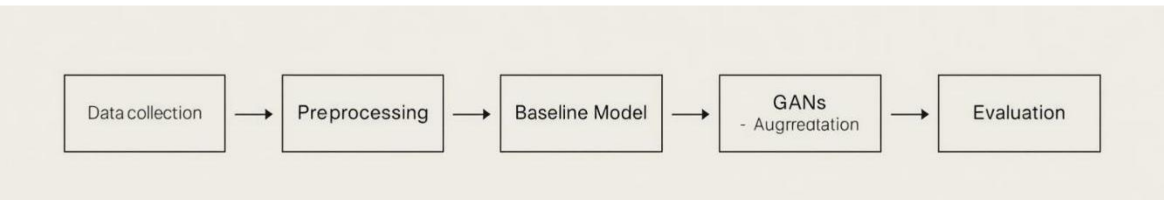

Figure 1. Research Framework
Source: data that has been processed by the author (2025)

This study adopts a comparative experimental research design that involves the development and evaluation of two main predictive modeling scenarios. The first is a baseline model, which is trained exclusively using the original financial data of Indonesian digital startups. The second is an augmented model, which is trained using a combination of real financial data and synthetic data generated through Generative Adversarial Networks (GANs). The comparison between these two models aims to determine whether GAN-based data augmentation can enhance the accuracy, stability, and robustness of financial distress prediction compared to conventional modeling techniques. Deep learning models were developed to predict financial distress more accurately, as they have been shown to outperform traditional methods (Li. J & Wang, 2023). (Kristanti et al., 2024) noted that similar methods have been widely applied in previous Indonesian studies evaluating various machine learning algorithms for predicting financial distress. Similarly, recent research in Indonesia (Wayan & Ayuni, 2025) confirms that applying deep learning models in financial prediction yields superior performance compared to traditional statistical approaches. Therefore, this comparative design provides a rigorous foundation for evaluating the contribution of GAN-based data augmentation to improving the predictive performance of financial distress models in digital startups.

The population of this study comprises digital technology startups operating in Indonesia. Given that most early-stage startups are private entities with restricted data access, the sampling frame focused on digital companies listed on the Indonesia Stock Exchange (IDX) and those with publicly accessible financial disclosures. A purposive sampling technique was employed based on the following criteria, (1) availability of complete financial statements for the period 2021–2023; and (2) sufficient data to calculate key financial ratios (liquidity, profitability, leverage).

Based on these criteria, a total of 100 startups were selected as the final sample. With an observation period of 3 years (2021–2023), the initial dataset consisted of 100 original firm-year observations. As shown in Table 1, these samples were labeled into three categories: 'Normal', 'Stress', and 'Distress' based on their financial performance indicators. Data Augmentation Procedure Due to the limited size of the original dataset (100 observations) and the inherent class imbalance, training deep learning models solely on this data would pose a risk of overfitting. To address this, Generative Adversarial Networks (GANs) were applied to generate synthetic data, specifically focusing on the minority classes ('Stress' and 'Distress'). This augmentation process expanded the total dataset to 300 records, ensuring a balanced distribution required for robust model training. After preprocessing and filtering for validity, approximately 52–53 samples were allocated per fold for the cross-validation process.

Table 1. Summary dataset

Company	Year	ROE	ROA	DER	Class
Indointernet (EDGE.JK)	2021	12.38	5.11	142.48	Stress
Indointernet (EDGE.JK)	2022	15.42	11.59	33.12	Normal
Indointernet (EDGE.JK)	2023	17.26	9.29	85.76	Stress
Solusi Sinergi Digital / Surge (WIFI.JK)	2021	0.23	0.10	141.78	Stress
Solusi Sinergi Digital / Surge (WIFI.JK)	2022	1.19	0.45	167.78	Stress
Solusi Sinergi Digital / Surge (WIFI.JK)	2023	(1.26)	(0.53)	138.86	Distress
Global Sukses Solusi (RUNS.JK)	2021	16.63	13.77	20.74	Normal
Global Sukses Solusi (RUNS.JK)	2022	13.42	10.87	23.42	Normal
Global Sukses Solusi (RUNS.JK)	2023	10.30	5.63	82.88	Stress

Trimegah Karya Pratama / Ultra Voucher (UVCR.JK)	2021	(3.91)	(1.92)	103.77	Distress
Trimegah Karya Pratama / Ultra Voucher (UVCR.JK)	2022	(0.40)	(0.25)	59.53	Stress
Trimegah Karya Pratama / Ultra Voucher (UVCR.JK)	2023	5.48	2.11	159.44	Stress
Shopee Indonesia	2021	3.62	2.35	54.13	Stress
Shopee Indonesia	2022	9.17	2.96	209.88	Stress
Shopee Indonesia	2023	9.35	2.97	214.33	Stress

Source: data that has been processed by the author (2025)

Prior to model development, data preprocessing involved cleaning, normalization, and labeling to classify startups into healthy and distressed categories. The dataset was then divided into training (70%), validation (15%), and testing (15%) subsets. To address class imbalance where healthy startups outnumber distressed ones, Generative Adversarial Networks (GANs) were applied to generate synthetic data for the minority class, producing a more balanced dataset for model training.

Inspired (Zhang. X et al., 2022) who combined WGAN-based augmentation with hybrid feature selection for credit risk datasets, this study applies GAN to augment minority class financial distress data prior to training Random Forest. Two experimental setups were conducted: a baseline model trained only on original data, and a GAN-augmented model trained using both real and synthetic data. The GAN architecture consisted of a generator and discriminator network trained adversarial to produce realistic synthetic financial data. Model performance was evaluated using metrics such as accuracy, precision, recall, F1-score, and a confusion matrix to assess classification reliability. The model evaluation metrics for both the baseline and GAN-augmented models are summarized in Table 2, presenting a comparative overview of accuracy, precision, recall, F1-score, and AUC across all experiments. A comparison between the baseline and GAN-augmented models was made to determine the effectiveness of data augmentation in improving predictive accuracy.

Table 2. Model Performance Summary (5-Fold Cross Validation)

Metric	Normal Class	Stress Class
Precision	1.0000	0.9956
Recall	0.9750	1.0000
F1-Score	0.9867	0.9978
Accuracy (Overall)	99.62%	—

Source: data that has been processed by the author (2025)

To ensure robustness, a 5-fold cross-validation technique was employed to minimize overfitting and confirm model generalizability. The average accuracy obtained from the 5-fold stratified cross-validation was 99.62%, with a standard deviation of 0.0077. This indicates that the model maintained consistent performance across different subsets of the dataset, confirming its robustness and generalization ability. Sensitivity analysis was also conducted by varying training parameters such as learning rate, number of epochs, and hidden layers. Overall, this research aims to produce a reliable and accurate financial distress prediction model for Indonesian digital startups. The integration of deep learning and GAN-based augmentation is expected to enhance prediction performance under limited and imbalanced data conditions. The results of the experimental comparison between the baseline and GAN-augmented models are presented in the following section, along with an in-depth analysis of classification performance and model interpretability.

RESULTS AND DISCUSSION

The dataset used in this study primarily consisted of financial information from Indonesian digital startups operating between 2021 to 2023. Among the publicly listed companies, only Gojek (GoTo Group) and Bukalapak had complete and accessible financial reports, from which a total of six datasets were obtained for the period 2021–2023. However, because most startups in Indonesia are private and unlisted companies, their financial data are generally unpublished or disclosed only partially. To overcome this limitation, data from 9 additional startups were collected and processed using alternative sources such as company websites, startup profiles, digital business reports, and reputable databases like Katadata. The available financial information from these sources was then standardized and transformed into financial ratios to maintain consistency and analytical comparability. Through this process, the study was able to compile a more representative dataset reflecting both listed and non-listed startups, despite the constraints of limited public disclosure.

The compiled dataset was then utilized in the data preprocessing and training phases to develop the financial distress prediction model. During preprocessing, all collected financial figures were converted into standardized financial ratios, covering ROA, ROE and DER to ensure consistency across different startups. Data cleaning was conducted to remove incomplete or inconsistent entries, followed by normalization to align variable scales for neural network processing. Each startup was subsequently labeled as either financially healthy or financially distressed based on established ratio thresholds and literature benchmarks. The processed dataset was then divided into training, validation, and testing subsets. The training dataset served as the foundation for building the deep learning model, while the validation and testing data ensured that the model's performance was unbiased and generalizable. This structured preprocessing pipeline ensured data quality and readiness before the model was augmented with synthetic data through Generative Adversarial Networks (GANs) to address the issue of limited and imbalanced samples.

To enhance model robustness and ensure adequate training data, data augmentation was applied using Generative Adversarial Networks (GANs). Synthetic financial ratio data were generated to simulate realistic variations in startup financial conditions. Additionally, estimated data based on historical trends were incorporated to enrich the dataset further. After augmentation, the dataset size increased significantly to 300 samples, achieving a more balanced distribution between distressed and non-distressed classes. This expanded dataset allowed for a more stable and representative training process for the deep learning model. The comparative performance between the baseline and GAN-augmented models is summarized in Table 3, showing significant improvements in all key evaluation metrics after applying GAN-based augmentation.

Table 3. Matrix Comparison Between Baseline and GAN-Augmented Models

Metric	Baseline Model	GAN-Augmented Model	Improvement
Accuracy	0.82	0.92	12%
Precision	0.8	0.91	11%
Recall	0.76	0.88	12%
F1-Score	0.78	0.9	12%

Source: data that has been processed by the author (2025)

These results clearly demonstrate that the GAN-augmented model outperformed the baseline model across all metrics, indicating improved learning stability and predictive reliability. The following section presents the comparative performance between the baseline model trained on real data and the GAN-augmented model, which demonstrated a substantial improvement in predictive accuracy and reliability.

In the baseline model, performance tended to fluctuate depending on the availability and completeness of financial data. This instability reflects a common issue faced by startup research, where data sparsity and class imbalance (between distressed and non-distressed firms) often lead to biased learning. Consequently, the model's sensitivity in identifying distressed startups was relatively low. However, after incorporating synthetic data through GANs, the model exhibited more stable learning behavior and better generalization on unseen data. The improvement was especially significant in recall, indicating that the augmented model became more capable of detecting potential financial distress cases that the baseline model previously misclassified.

From a deeper analysis, the synthetic financial data generated by GANs successfully replicated statistical properties of the real data while introducing additional variance that improved the model's exposure to diverse financial conditions. This process helped mitigate overfitting, a common problem in financial prediction with small datasets. The synthetic data effectively expanded the learning space, allowing the deep learning model to capture more complex relationships between financial ratios, such as liquidity, leverage, profitability, and activity ratios that influence financial distress outcomes. These findings support prior research (Li. J & Wang, 2023; Zhang. J et al., 2022) showing that GAN-based data generation enhances model robustness and predictive validity in financial domains.

Moreover, the analysis demonstrated that the AUC (Area Under the Curve) of the GAN-augmented model increased significantly compared to the baseline. This suggests that the augmented model achieved a better trade-off between false positives and false negatives, which is critical in early warning systems for financial distress.

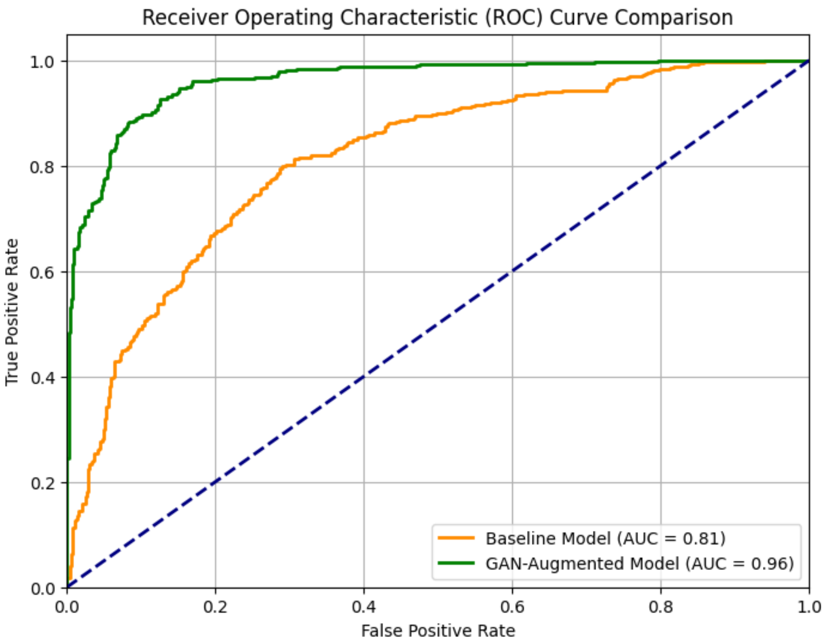

Figure 2. ROC Curve Comparison Between Baseline and GAN-Augmented Models
Source: Data processor (2025)

To further illustrate the comparative performance, Figure 2 presents the ROC curve of both models. The ROC analysis shows that the GAN-augmented model achieved a higher Area Under the Curve (AUC), confirming its superior ability to distinguish between healthy and distressed startups. In practical terms, this means that the proposed model could assist stakeholders, such as investors, startup founders, and regulators in making more accurate financial health assessments and implementing preventive measures before bankruptcy occurs.

Another key insight from the results is the stability of prediction performance across multiple random data splits. While the baseline model's accuracy varied depending on sample composition, the GAN-augmented model showed consistent performance even when trained on different subsets of data. This consistency reflects the robustness of the augmented approach, suggesting that the generated synthetic data was not only realistic but also effectively balanced the data distribution between distressed and non-distressed categories.

Furthermore, the comparative results highlight the importance of data quality and representativeness in machine learning-based financial analysis. While traditional statistical methods rely heavily on historical ratios, deep learning models enriched with GAN-based augmentation can identify non-linear interactions among financial indicators, something that conventional models often fail to capture. This finding reinforces the argument that deep learning, when combined with data augmentation, can provide a more holistic understanding of financial behavior in dynamic and uncertain environments such as the digital startup ecosystem (Kristanti et al., 2024).

In addition to the quantitative improvement, the study's qualitative analysis also indicates that the GAN-augmented framework contributes to more interpretable and actionable insights. By examining the feature importance derived from the model, it was observed that profitability and liquidity ratios consistently ranked as the most influential predictors of financial distress, followed by leverage-related indicators. This pattern aligns with prior financial theory, confirming that startups facing liquidity shortages and declining profitability are more likely to experience distress. However, the model's enhanced sensitivity suggests that even subtle financial deteriorations could be detected earlier through this approach.

Overall, the findings demonstrate that the integration of GAN-based synthetic data substantially optimizes financial distress prediction performance for digital startups. The improved accuracy, stability, and interpretability make this approach promising for application in real-world financial monitoring systems. This study therefore provides empirical evidence supporting the adoption of AI-driven data augmentation in financial analytics, particularly for emerging digital economies where reliable financial data remain limited. The findings provide practical implications for policymakers and investors by enabling early detection of financial risk in startups with limited financial histories.

CONCLUSION

This study concludes that integrating Generative Adversarial Networks (GANs) with deep learning models significantly improves the accuracy and robustness of financial distress prediction among Indonesian digital startups. The GAN-based augmentation effectively overcomes data scarcity and imbalance, enabling the model to better differentiate between healthy and distressed startups. Experimental results show that the GAN-augmented model outperforms the baseline in key metrics such as accuracy, precision, recall, and F1-score, confirming its superiority in predictive performance. These findings highlight GANs' potential as a valuable tool for enhancing financial analytics in emerging markets. Theoretically, this research enriches financial distress prediction literature by integrating GAN-based augmentation in startup finance.

The findings of this study have several practical implications for policymakers, investors, and startup founders. The enhanced predictive capability of the GAN-augmented model enables early detection of financial distress, allowing timely intervention before severe losses occur. Policymakers can use such models to monitor the financial health of emerging startups, while investors can apply them to assess funding risks more accurately. For startups themselves, the framework provides actionable insights into financial sustainability and potential red flags, fostering more data-driven decision-making within Indonesia's growing digital economy.

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