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# Autoencoder Based Anomaly Detection of Indonesia's Leading Banks

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***Abstract***

This study This study builds and tests an autoencoder model that hunts for multivariate anomalies inside the financial data of Indonesia's banking sector. Three issuers anchor the analysis, PT Bank Mandiri (Persero) Tbk (BMRI), PT Bank Rakyat Indonesia (Persero) Tbk (BBRI) and PT Bank Central Asia Tbk (BBCA). The goal is not fraud detection in the narrow sense but something broader, isolating financial behavior that breaks the pattern investors expect and that might signal deeper trouble. The method layers three techniques. Correlation analysis maps how variables move together. Z Score standardization exposes univariate outliers. An autoencoder trained on an 80 to 20 split between training and test data hunts for anomalies that only reveal themselves across several variables at once. On the test set, BMRI and BCA produced zero anomalies and earned a low-risk label. BBRI stood apart. It logged two anomalies out of thirteen test observations, a rate of 15.38 percent that places it in the moderate risk bracket. Both anomalous quarters, the fourth quarter of 2008 and the first quarter of 2011, trace back to sharp swings in the Z Scores for Revenue, Net Income, Operating Cash Flow, Investing Cash Flow and Financing Cash Flow. The results argue for the autoencoder as a genuinely capable tool for multivariate anomaly detection in financial data. They offer real insight into how issuer risk profiles differ. Still, the test set is small. That limits how far these conclusions should be generalized.
**Keywords:** Anomaly Detection, Autoencoder, Risk Category, Fundamentals, Investment

**Abstrak**

Studi ini membangun serta menguji model autoencoder untuk melacak anomali multivariat dalam data keuangan sektor perbankan Indonesia dengan menjadikan PT Bank Mandiri (Persero) Tbk (BMRI) PT Bank Rakyat Indonesia (Persero) Tbk (BBRI) dan PT Bank Central Asia Tbk (BBCA) sebagai subjek analisis utama. Tujuan utamanya bukan sekadar mendeteksi kecurangan melainkan mengisolasi pola perilaku keuangan yang menyimpang dari ekspektasi investor serta berpotensi mengindikasikan masalah yang lebih mendalam. Metode yang digunakan menggabungkan analisis korelasi untuk memetakan pergerakan variabel standar Z-Score untuk mendeteksi outlier univariat dan autoencoder dengan pembagian data latih serta data uji 80 banding 20 guna menemukan anomali yang hanya muncul melalui interaksi antarvariabel. Hasil pengujian menunjukkan bahwa BMRI dan BBCA tidak memiliki anomali sehingga dikategorikan sebagai bank berisiko rendah. Sebaliknya BBRI mencatatkan dua anomali dari tiga belas observasi atau sekitar 15,38 persen yang menempatkannya dalam kategori risiko moderat. Kedua anomali tersebut terjadi pada kuartal keempat tahun 2008 serta kuartal pertama tahun 2011 akibat lonjakan tajam pada Z-Score Pendapatan Laba Bersih serta arus kas Operasi Investasi dan Pendanaan. Temuan ini memperkuat posisi autoencoder sebagai perangkat yang andal untuk mendeteksi anomali multivariat dalam data keuangan sekaligus memberikan wawasan nyata mengenai profil risiko emiten meskipun keterbatasan jumlah data uji membuat hasil penelitian ini harus disikapi dengan bijak sebelum digeneralisasi lebih luas.
**Kata Kunci:** Deteksi Anomali, Autoencoder, Kategori Risiko, Fundamental, Investasi



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## INTRODUCTION

Fundamental analysis anchors how investors judge a stock's true worth and decide whether to buy (Zulkifli, 2023). The method forces a hard look at a company's financial statements, especially the balance sheet and the income statement, to gauge stability and real value (Rajeswari, 2020; Zulkifli, 2023). Investors weigh revenue growth, profitability and market position when they size up how attractive a company looks as an investment (Viktorovich, 2024). That scrutiny stretches across the whole economy, drills into specific industries and lands on individual firms. It lets investors separate stocks that trade below their worth from those that trade above it (Viktorovich, 2024). For retail investors in particular, fundamental analysis is the discipline that keeps bad decisions in check (Rajeswari, 2020). Many pair it with technical analysis, reading charts and patterns to catch what the market is doing in real time (Wadiwala, 2021). Put the two together and portfolio construction sharpens considerably across assets as varied as stocks, bonds and mutual funds (Wadiwala, 2021).

Anomaly detection inside financial systems reaches well past fraud. It catches a wide range of irregular behavior that hints at risk building somewhere in the system (Pinto & Sobreiro, 2022). Behavioral tendencies and market anomalies steer investor decisions more than most models admit. Financial literacy moderates how strongly they do (Abideen et al., 2023). Artificial intelligence methods, autoencoder and isolation forest chief among them, now see growing use for anomaly detection in financial services because they flag outliers and cut financial risk in ways manual review cannot (Tyagi et al., 2025). The autoencoder in particular has proven itself across a wide range of domains. Hasan Torabi and colleagues (2023) built a method on vector reconstruction error that lifted detection performance inside cloud computing networks. Zhen Cheng and colleagues (2021) pushed unsupervised anomaly detection further with an improved autoencoder (IAEAD) that reshapes the feature space and ties an anomaly specific loss to the reconstruction loss. In an industrial setting, T. Tziolas and colleagues (2022) showed that an autoencoder combining long short-term memory with convolutional neural networks surfaces anomalies inside multivariate time series data. D. Lappas and colleagues (2021) folded Fourier Transforms into an autoencoder and found that frequency domain features sharpen anomaly detection across datasets. Line these studies up and a clear picture emerges. The autoencoder adapts to almost any data shape and stays efficient while doing it.

Evaluating an investment properly keeps risk down and returns up. That evaluation has to cover incoming cash flow, profitability and a spread of risk factors (Zhykharieva & Kozyr, 2022). Free cash flow, debt management and profitability shape an investment's prospects the most, with debt management carrying the heaviest weight (Wahyuni, 2021). Anyone weighing an investment needs to read profit margins alongside systematic risk, since the two vary sharply from sector to sector (Rachmawati et al., n.d.). Profitability and capital structure move investment risk in measurable ways, while liquidity barely registers (Caroline et al., 2023). A careful evaluation, sensitivity and scenario analysis included, helps investors keep risk in check (Zhykharieva & Kozyr, 2022). Sharper financial awareness helps them dodge fraud and make sounder calls (Caroline et al., 2023).

This study hunts for anomalies inside the fundamental data of Indonesia's three largest banks, Bank Mandiri, Bank BRI and Bank BCA. These three banks carry outsized strategic weight in the national banking landscape, a fact that mirrors a broader pattern of asset concentration across the industry, visible in Indonesia through the sheer share of total commercial bank assets the top three banks hold between them. That concentration is widely credited with supporting overall efficiency in the banking sector. That is precisely why anomalies at these leading banks deserve close scrutiny. The point is not only to surface problems or opportunities at each institution but to build risk categories sharp enough to matter. The resulting risk groupings should help investors make better decisions, especially when they manage portfolios inside a banking sector that carries real systemic weight.

## METHODS

This section outlines the research methodology by addressing three core components. We first define the research variables used to assess financial performance. Next, we describe the data collection process that provides the historical foundation for this study. Finally, we detail the autoencoder theory to explain how the model detects multivariate anomalies.

### *Research Variables*

The data behind this study is secondary and comes from the historical financial statements of three major Indonesian banks. Beyond the raw figures pulled straight from those statements, the study calculates several financial ratios and additional performance indicators too. These serve as extra variables that let the autoencoder model capture each company's performance and financial condition in real depth.

The key variables drawn from the financial statements run as follows:

1. Net Income (NI) stands as the main gauge of a company's profitability.
2. Revenue captures the total money a company brings in through its operations.
3. Operating Cash Flow (OCF) tracks cash generated by the company's core business activities.
4. Financing Cash Flow covers cash tied to debt, equity and dividends.
5. Investing Cash Flow covers cash tied to buying or selling long term assets. Building on these five, the derived variables add further texture.

Building on these five, the derived variables add further texture:

1. Reinvestment Ratio measures the share of earnings a company keeps and puts back into the business to fuel future growth.

$$ReinvestmentRatio = \frac{Operating\ Cash\ Flow}{Investing\ Cash\ Flow}$$

(Shan & Jiao, 2022)

2. Cash Conversion Ratio measures how effectively a company turns reported net income into real operating cash flow.

$$Cash\ Conversion\ Ratio = \frac{Operating\ Cash\ Flow}{Net\ Income}$$

(Samosir et al., 2022)

3. Operating Cash Flow Margin measures operating cash flow generated per unit of revenue, a gauge of operational efficiency.

$$OCF\ Margin = \frac{Operating\ Cash\ Flow}{\text{Revenue}}$$

(Tambunan & Lubis, 2024)

4. Annual operating cash flow growth tracks the health of operating cash over time.

$$OCF\ Growth = \frac{(OCF_t - OCF_{t-1})}{OCF_{t-1}}$$

(Nurhusni, 2022)

5. Annual Net Income Growth captures how fast a company's net income rises each year, a marker of profitability trends.

$$Net\ Income\ Growth = \frac{(NI_t - NI_{t-1})}{NI_{t-1}}$$

(Rahmawati & Tristiarto, 2023)

6. Net Income Volatility, the standard deviation of net income over the observation period, captures swings in profitability.

$$Net\ Income\ Volatility = \sigma\ Net\ Income$$

(Bao et al., in press)

where $\sigma$ stands for standard deviation.

7. Operating Cash Flow Volatility, the standard deviation of operating cash flow over the observation period, captures how stable core activity cash flow really is:

$$OCF\ Volatility = \sigma\ OCF$$

(Bao et al., in press)

where $\sigma$ stands for standard deviation.

8. The Z Score, built on the Altman Z Score framework, rounds out the key variables as a broad indicator of financial health and potential risk (Bao et al., in press).

***Data Collection***

The secondary data collected runs quarterly and covers Indonesia's three largest banks, PT Bank Mandiri (Persero) Tbk (BMRI), PT Bank Rakyat Indonesia (Persero) Tbk (BBRI) and PT Bank Central Asia Tbk (BBCA), pulled from the Financial menu on the Stockbit website. Quarterly granularity gives a deeper read and more frequent observations into each bank's financial dynamics than annual data ever could. The data spans the first quarter of 2008 through the last quarter of 2024. Before the Autoencoder process began, the analysis replaced zero values with the mean of that data. No missing values turned up for any of the key variables during collection.

***Autoencoder***

An autoencoder is a feed forward neural network trained to turn its input back into an output. Inside it sits a hidden layer representing a code, often called a feature, that captures a nonlinear representation of the input data. Two components do the work, an encoding function $f_w(.)$ and a decoding function $g_u(.)$. The network learns a code from the input through these two steps, encoding and decoding.

$$\hat{x} = g_u(f_w(x)) \quad (1)$$

Here $x$ is the input data and $\hat{x}$ is the reconstructed version of it. The basic idea trains $f_w(.)$ and $g_u(.)$ so the gap between $x$ and $\hat{x}$ shrinks as far as it can.

$$\min_{u,w} \|x - \hat{x}\| \quad (2)$$

Allowing multiple network layers for the encoder and the decoder builds an effective deep autoencoder capable of representing complex input data. The anomaly detection approach built around an autoencoder on a simple idea. Anomalies carry higher reconstruction loss while normal data carries lower reconstruction loss. That is why reconstruction loss serves as the standard anomaly measure in most autoencoder anomaly detection methods. Given an input xi, once the autoencoder finishes training on the training set, the anomaly score for xi can be written as

$$S(x_i) = \|x_i - \hat{x}_i\| \quad (3)$$

Here $\|.\|$ typically gets set as the $\ell_2$ norm or the $\ell_1$ norm [22].

## RESULT AND DISCUSSION

Unpacking the data starts with the Pearson correlation matrix for both the key and derived variables. Correlation shows how closely two variables track each other. Reading these patterns matters because anomalies can spring not just from an extreme value in one variable but from a breakdown in the correlation relationships variables are expected to follow.

**Figure 1.** Heatmap of BMRI Key Variables

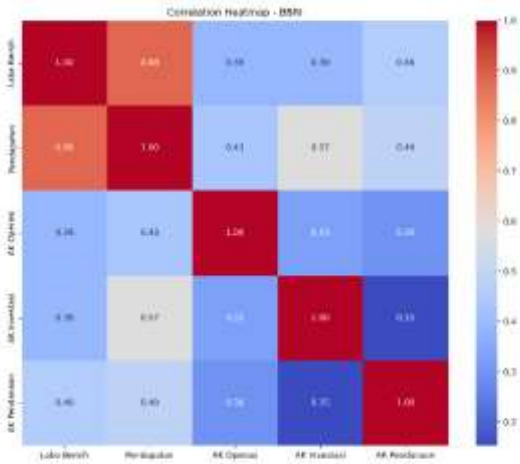

**Figure 2.** Heatmap of BBRI Key Variables

**Figure 3.** Heatmap of BBCA Key Variables

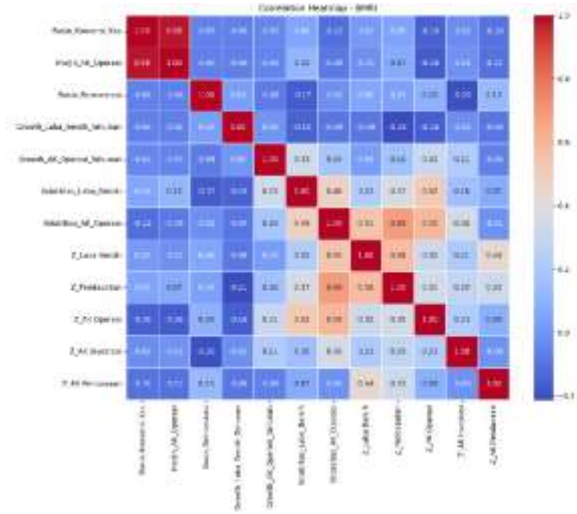

**Figure 4.** Heatmap of BMRI Derived Variables

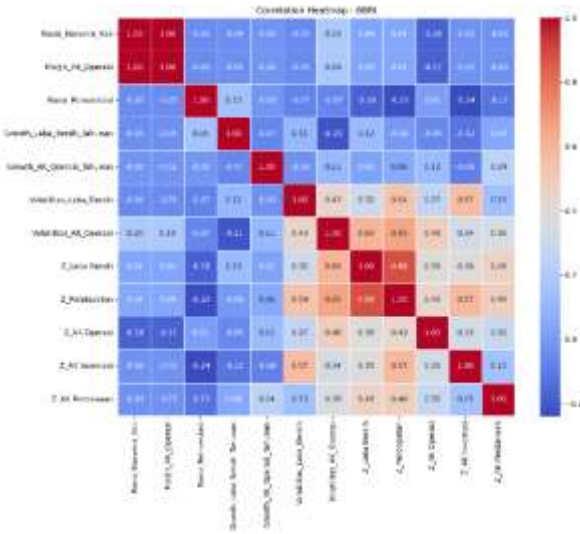

**Figure 5.** Heatmap of BBRI Derived Variables

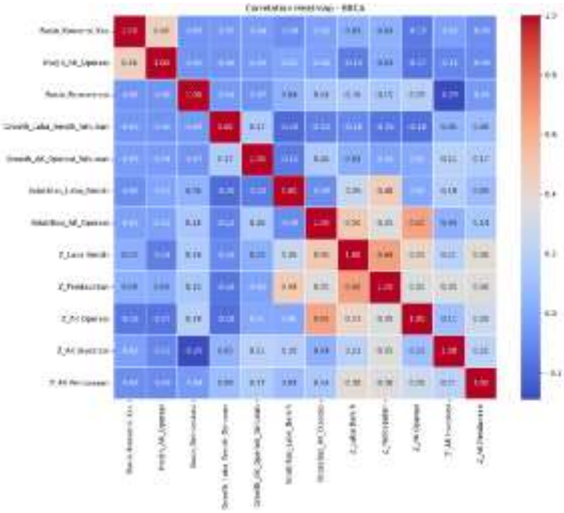

**Figure 6.** Heatmap of BBCA Derived Variables

First, get a solid read on how each feature is distributed and to flag the outliers worth watching. The analysis converted the key variables to Z Scores for this, a step that puts variables sitting on very different scales onto comparable footing. The boxplots that follow show the Z Score distribution for Net Income, Revenue, Operating Cash Flow, Investing Cash Flow and Financing Cash Flow across the three banks BMRI, BBCA and BBRI.

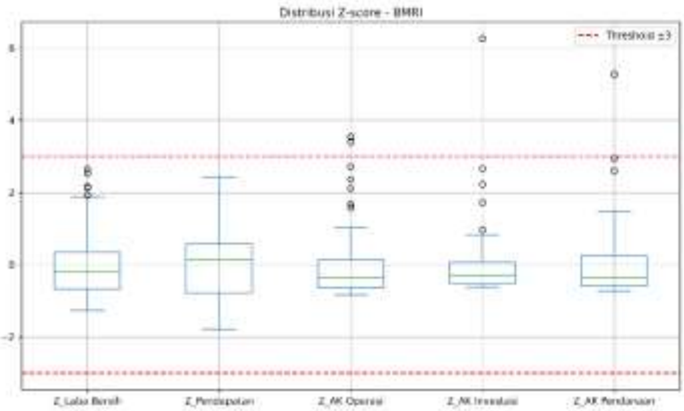


**Figure 7.** Z Score Distribution of BMRI Key Variables

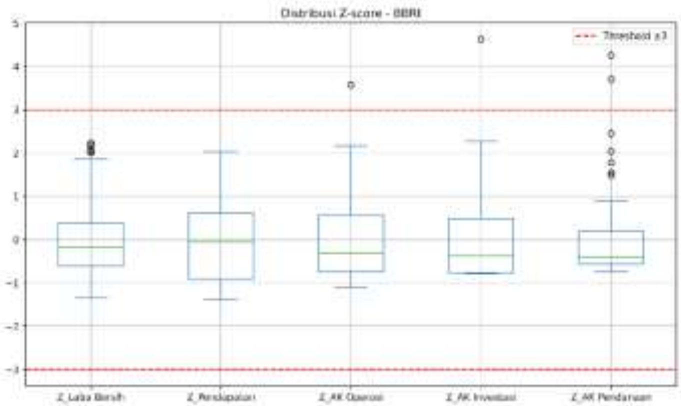


**Figure 8.** Z Score Distribution of BBRI Key Variables

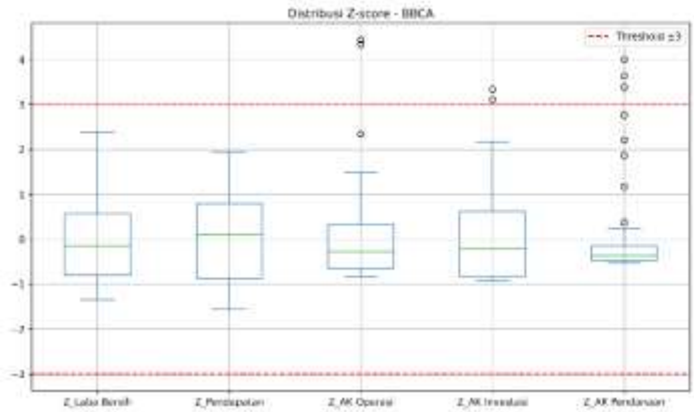


**Figure 9.** Z Score Distribution of BBCA Key Variables

With the correlation and distribution picture in hand, the analysis moves to the Autoencoder stage. Recognizing anomalies with a Vanilla Autoencoder comes down to computing reconstruction error and setting a threshold for flagging anomalies. Once the autoencoder finishes training on 80 percent of the data, the analysis calculates reconstruction error on the remaining 20 percent, the test set. A high reconstruction error means the autoencoder struggled to reconstruct that data. That struggle is a strong signal something sits off. The figures below show the vanilla autoencoder outputs for BMRI, BBRI and BBCA in turn.

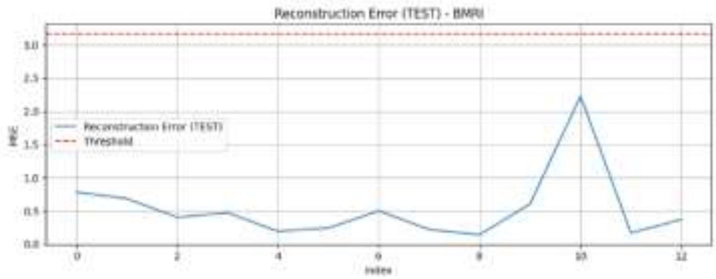


**Figure 10.** Autoencoder Results for BMRI

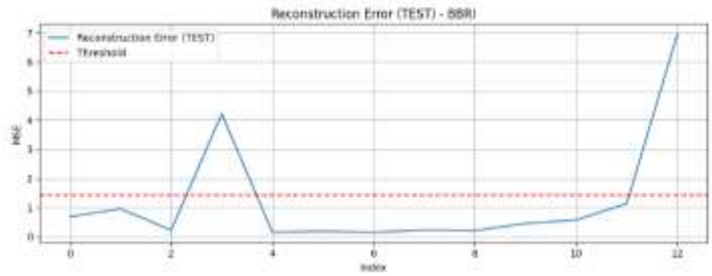


**Figure 11.** Autoencoder Results for BBRI

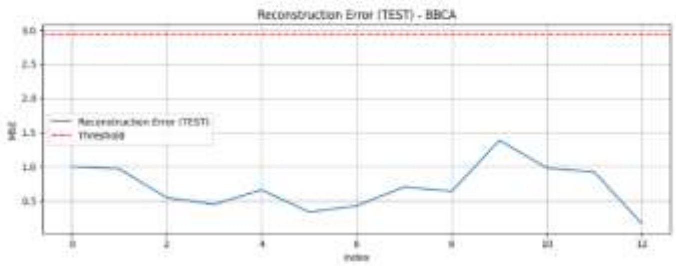


**Figure 12.** Autoencoder Results for BBCA

The heatmap in Figure 4 for BMRI flags several notably strong relationships on both sides of the ledger. The Cash Conversion Ratio and the Operating Cash Flow Margin move in near lockstep at 0.980951. Operating Cash Flow Volatility tracks the Revenue Z Score closely at 0.682871 and the Operating Cash Flow Z Score moderately at 0.589263, which in plain terms means bigger swings in operating cash flow line up with higher revenue and operating cash flow Z Scores. The negative side tells a far quieter story. Annual Net Income Growth barely tracks the Revenue Z Score at negative 0.212195. The Reinvestment Ratio barely tracks the Investing Cash Flow Z Score at negative 0.201232 and Net Income Volatility at negative 0.168424, weak enough on both counts to be essentially inconsequential.

For BBRI in Figure 5, the Cash Conversion Ratio and the Operating Cash Flow Margin move almost perfectly together at 0.999768. The Net Income and Revenue Z Scores link tightly too at 0.881595. Operating Cash Flow Volatility tracks the Revenue Z Score fairly closely at 0.653944. Nothing on the negative side stands out. The Reinvestment Ratio barely tracks the Investing Cash Flow Z Score at negative 0.238499 and the Revenue Z Score at negative 0.231005. Annual Net Income Growth barely tracks Operating Cash Flow Volatility at negative 0.211246, none of it amounting to much. For BBCA in Figure 6, the strongest positive link sits between the Net Income and Revenue Z Scores at 0.655360, followed by Operating Cash Flow Volatility and the Operating Cash Flow Z Score at 0.646282 and, more loosely, Operating Cash Flow Volatility and the Net Income Z Score at 0.496001. The negative side stays uniformly weak. The Reinvestment Ratio's mildest negative link sits with the Investing Cash Flow Z Score at negative 0.288813. Annual Net Income Growth barely tracks Net Income Volatility at negative 0.197605 and the Operating Cash Flow Z Score at negative 0.182949, again nothing meaningful.

Comparing the Z Score distributions across the three banks answers a question worth asking. Is an anomaly at one bank a one off event, or does it belong to a wider pattern across the industry? This univariate view offers a first read on possible anomalies variable by variable, but univariate and multivariate anomalies do not always line up. A multivariate anomaly can hide entirely from univariate analysis if it stems from how variables interact rather than from any single extreme value.

Figure 7's boxplot of the Z Score distribution for BMRI's main variables shows most data clustered near the mean at Z Score zero, but a handful of observations sit beyond three standard deviations in either direction, a sign of possible univariate outliers. A clear outlier shows up in the Operating Cash Flow Z Score above 3, another in the Investing Cash Flow Z Score above 6 and a third in the Financing Cash Flow Z Score above 4, all signs of an unusually active stretch in those variables. Bank BBRI in Figure 8 tells a similar story. A clear outlier shows up in the Operating Cash Flow Z Score above 3, another in the Investing Cash Flow Z Score above 4 and a third in the Financing Cash Flow Z Score above both 3 and 4. BBCA in Figure 9 shows univariate outliers of its own, a clear one in the Operating Cash Flow Z Score above 4, another in the Investing Cash Flow Z Score above 3 and a third in the Financing Cash Flow Z Score above both 3 and 4.

The autoencoder trained on 80 percent of the data and then met a test on the remaining 20 percent, data it had never seen before, a setup built to produce anomaly detection that holds up in practice and reflects how well the model would catch deviations in genuinely new data. Risk profiles on the test set varied sharply across issuers. BMRI turned up no anomalies at all across thirteen test observations and earned a Low risk classification. BCA matched that result exactly, also zero anomalies out of thirteen, also Low risk. BBRI stood apart with two anomalies out of thirteen test observations, a rate of 15.38 percent that places it in the Moderate risk bracket. BBRI's two anomalies fell in different quarters. The first, in the fourth quarter of 2008, carried a Mean Squared Error of 4.21, driven by a Revenue Z Score of negative 1.28, a Net Income Z Score of negative 1.27, an Operating Cash Flow Z Score of negative 0.89, an Investing Cash Flow Z Score of negative 0.78 and a Financing Cash Flow Z Score of negative 0.62, all negative and all pointing to a broad dip in financial performance that quarter. The second, in the first quarter of 2011, carried a higher MSE of 6.95, with the Revenue Z Score at negative 1.01, the Net Income Z Score at negative 0.89, the Investing Cash Flow Z Score at negative 0.78 and the Financing Cash Flow Z Score at negative 0.72 all sitting negative even as the Operating Cash Flow Z Score came in positive at 0.75. Read together, these figures trace a multivariate pattern that strays from the normal baseline the autoencoder had learned, even where a single variable on its own looked perfectly fine. The anomalies flagged for BBRI in the fourth quarter of 2008 and the first quarter of 2011 point to a real deviation in the multivariate pattern the autoencoder picked up on. Both quarters most likely mark genuine operational events at BBRI. Both pushed the reconstruction error well past what counts as normal.

## CONCLUSION

Trained on an 80 to 20 split, the autoencoder model proved highly effective at catching anomalies in test data it had never encountered. That result gives a solid read on each issuer's risk profile. BMRI and BCA came up clean on the test data, zero anomalies each, landing both in the Low risk bracket. BBRI told a different story. Two anomalies out of thirteen test observations, a 15.38 percent anomaly rate and a place in the Moderate risk category. Those anomalies trace back to the fourth quarter of 2008 and the first quarter of 2011, both marked by sharp swings in the Revenue, Net Income, Operating Cash Flow, Investing Cash Flow and Financing Cash Flow Z Scores, signs of a meaningful performance dip or an unusual pattern in those periods. The autoencoder, on this evidence, earns its place as a genuinely powerful tool for anomaly detection in finance, even though the small test set here means the results deserve caution before anyone stretches them further. What they do offer is a real window into how a banking issuer's risk profile shows up inside multivariate financial data behavior.

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