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Predicting Mutual Fund Stress Levels Utilizing SEBI's Stress Test Parameters in MidCap and SmallCap Funds Using Deep Learning Models

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Abstract: The Association of Mutual Funds of India (AMFI), under the direction of the Securities and Exchange Board of India (SEBI), provided open access to various risk parameters with respect to MidCap and SmallCap funds for the first time from February 2024. Our study utilizes AMFI datasets from February 2024 to September 2024 which consisted of 14 variables. Among these, the primary variable identified in grading mutual funds is the stress test parameter, expressed as number of days required to liquidate between 50% and 25% of the portfolio, respectively, on a pro-rata basis under stress conditions as a response variable. The objective of our paper is to build and test various neural network models which can help in predicting stress levels with the highest accuracy and specificity in MidCap and SmallCap mutual funds based on AMFI's 14 parameters as predictors. The results suggest that the simpler neural network model architectures show higher accuracy. We used Artificial Neural Networks (ANN) over other machine learning methods due to its ability to analyze the impact of dynamic interrelationships among 14 variables on the dependent variable, independent of the statistical distribution of parameters considered. Predicting stress levels with the highest accuracy in MidCap and SmallCap mutual funds will benefit investors by reducing information asymmetry while allocating investments based on their risk tolerance. It will help policy makers in designing controls to protect smaller investors and provide warnings for funds with unusually high risk.

Keywords: stress test; liquidity analysis; risk management; mutual funds; neural networks; deep learning

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1. Introduction

The growth of mutual funds in India has been remarkable in recent years. Growing participation from retail investors can be attributed to several factors, including increasing financial awareness, favourable regulatory measures, and the attractiveness of mutual funds as a convenient and accessible investment avenue. The proliferation of mutual fund offerings and the democratization of investment access has opened new avenues for investors to participate in capital markets. As a result, mutual funds emerged as preferred investment vehicles, catering to the diverse investment objectives and risk profiles of investors across the spectrum. The mutual fund sector in India has witnessed a surge in retail investor participation, as per the AMFI data released for January 2024. MidCap funds have 13 million portfolios with an investment of INR 29 million. SmallCap funds account for 17.8 million portfolios with a value of INR 24.7 million.[1] One of the key drivers behind the surge in retail investor participation in mutual funds is the advent of systematic investment plans (SIPs), which have revolutionized the way retail investors approach mutual fund investments (Kavya and Chokkamreddy 2024). SIPs offer a disciplined and hassle-free approach to wealth accumulation, allowing both seasoned investors and newcomers alike to contribute small amounts at regular intervals. This systematic approach not only helps in mitigating market volatility, but also inculcates financial discipline among investors, encouraging them to stay invested for the long term. As a result, mutual fund Assets Under Management (AUM) have witnessed a steady uptrend, reflecting the evolving preferences of investors seeking diversified and professionally managed investment avenues (Narasimha 2024; Joshi and Arora 2022; Sukumar 2020).

Furthermore, regulatory initiatives aimed at enhancing transparency and investor protection have bolstered investor confidence in mutual funds. Measures such as the categorization and rationalization of mutual fund schemes, along with stringent disclosure norms, have contributed to greater trust and credibility in the mutual fund industry. As a result of these concerted efforts, India has witnessed a significant uptick in retail investor participation in mutual funds. The democratization of investment access, coupled with robust investor education initiatives, has empowered individuals from diverse backgrounds to take charge of their financial futures and embark on the journey of wealth creation through mutual funds (Berk and van Binsbergen 2012; Li and Rossi 2020; Patton and Timmermann 2010). The onset of the global COVID-19 pandemic brought about unprecedented volatility and uncertainty in financial markets worldwide, including in India. Despite initial market turbulence, the mutual fund industry in India showcased resilience and adaptability, as evidenced by the sustained growth in AUM across various schemes. This resilience is attributable to the robust regulatory framework, proactive measures by fund managers, and the enduring trust of investors in the mutual fund ecosystem (Narasimha 2024).

However, despite the progress made, there remains a pressing need for continued awareness and education initiatives to ensure that investors make informed investment decisions. As retail investors navigate the complexities of the financial markets, it is imperative to equip them with the knowledge and tools necessary to identify suitable investment opportunities and manage risk effectively (Elton and Gruber 2020; Jones and Mo 2020; Pástor et al. 2017; Feng et al. 2020).

This investment frenzy among retail investors in MidCap and SmallCap funds has not gone unnoticed by market regulators like the Securities Exchange Board of India (SEBI). Concerned about potential risks to retail investors amidst soaring market valuations, SEBI has initiated various steps to safeguard investor interests in these funds (Joshi and Arora 2022). In response to SEBI's directives, AMFI has taken some very bold steps such as tasking the trustees of all Asset Management Companies (AMCs) with framing policies to protect investors in MidCap and SmallCap schemes. The policies being formulated by the trustees, in consultation with the Unitholder Protection Committees of the AMCs, are designed to incorporate proactive measures to shield investors from potential risks. These measures also include moderating inflows into MidCap and SmallCap funds, portfolio rebalancing, and enhancing the disclosure of risk parameters and stress tests (Hoberg et al. 2018). The rationale behind these regulatory measures lies in the unprecedented returns witnessed by MidCap and SmallCap indices in recent times, coupled with heightened market volatility due to global events. The surge in investor inflows has led to inflated valuations, raising concerns about market stability and investor protection (Irvine et al. 2018). Hence, SEBI and AMFI are taking proactive steps to ensure that fund houses are adequately prepared to navigate market uncertainties and protect the interests of retail investors. Through these measures, they aim to uphold market integrity and promote investor confidence in India's mutual fund industry.

Given this outlook, recently, the landscape of mutual fund investments in India has witnessed a notable transformation, marked by the introduction of innovative methodologies for evaluating fund performance and risk. One such significant development is the initiative undertaken by the Association of Mutual Funds of India (AMFI), Mumbai, India to assess stress levels in MidCap and SmallCap mutual funds, referred to as the "Stress Test". The test involves simulating scenarios where a significant number of investors demand redemption, thereby assessing how quickly a fund can meet redemption requests from investors. For both MidCap and SmallCap funds, liquidation of either 25 percent or

50 percent of the portfolio on a pro-rata basis and the time taken to meet the liquidation request are considered in the dataset. Importantly, the stress test allows for fund managers to exclude the bottom 20 percent of the portfolio based on liquidity considerations. This provision enables fund managers to retain stocks deemed to be essential for long-term gains, enhancing the flexibility and strategic management of the portfolio. This initiative represents a proactive step towards enhancing transparency and accountability within the mutual fund industry, aiming to provide investors with deeper insights into the resilience of their investment portfolios.

The volatility and unpredictability of financial markets pose significant challenges for investors, particularly in assessing the stress levels of mutual funds. While SEBI has outlined a methodology for stress testing mutual funds, there remains a need for advanced analytical tools to accurately predict the stress levels of mutual funds, particularly in the MidCap and SmallCap segments. Traditional approaches may lack the sophistication and predictive power needed to navigate the complexities of modern financial markets. To overcome that limitation, we test various neural network models which can help in predicting stress levels with the highest accuracy and specificity in MidCap and SmallCap mutual funds based on AMFI's parameters as predictors.

We also test the effectiveness and reliability of the models to provide actionable insights and recommendations to aid investors and fund managers in managing risk and optimizing portfolio strategies. The next two sections provide details on data collection and research methodology, followed by data analysis and interpretation. Finally, last section provides conclusion and scope for future research.

2. Data Collection

For our study, the stress test data were sourced from the AMFI website's dedicated section, "Disclosure of Stress Test & Liquidity Analysis in respect of MidCap & SmallCap Funds". Specifically, stress test data pertaining to MidCap and SmallCap mutual funds for the period of eight months from February 2024 to September 2024 were collected. The number of mutual funds that were part of the dataset from February 2024 to September 2024 is provided in Table 1.

Table 1. Number of mutual funds as part of monthly stress test datasets.

Month	MidCap Funds	SmallCap Funds
February to September 2024 (except May 2024)	29	27
May 2024	13	10

Source: Compiled from www.amfiindia.com.

Table 1 shows that between February and September 2024; the dataset included information of 29 MidCap funds and 27 SmallCap funds. In May 2024, data were available for only 13 MidCap funds and 10 SmallCap funds. The MidCap and SmallCap mutual funds that were part of the dataset from February 2024 to September 2024 are provided in Tables 2 and 3, respectively.

Table 2. List of MidCap mutual funds, part of dataset (from February to September 2024) [1].

Sl. No	MidCap Mutual Funds	February 2024	March 2024	April 2024	May 2024	June 2024	July 2024	August 2024	September 2024
1	Aditya Birla Sun Life MidCap Fund	✓	✓	✓	X	✓	✓	✓	✓
2	Axis MidCap Fund	✓	✓	✓	X	✓	✓	✓	✓
3	Bandhan MidCap Fund	✓	✓	✓	✓	✓	✓	✓	✓
4	Baroda BNP Paribas MidCap Fund	✓	✓	✓	X	✓	✓	✓	✓

Table 2. *Cont.*

Sl. No	MidCap Mutual Funds	February 2024	March 2024	April 2024	May 2024	June 2024	July 2024	August 2024	September 2024
5	Canara Robeco MidCap Fund	✓	✓	✓	✓	✓	✓	✓	✓
6	DSP MidCap Fund	✓	✓	✓	X	✓	✓	✓	✓
7	Edelweiss MidCap Fund	✓	✓	✓	✓	✓	✓	✓	✓
8	Franklin India Prima Fund	✓	✓	✓	X	✓	✓	✓	✓
9	HDFC MidCap Opportunities Fund	✓	✓	✓	X	✓	✓	✓	✓
10	HSBC MidCap Fund	✓	✓	✓	✓	✓	✓	✓	✓
11	ICICI Prudential MidCap Fund	✓	✓	✓	X	✓	✓	✓	✓
12	Invesco India MidCap Fund	✓	✓	✓	X	✓	✓	✓	✓
13	ITI MidCap Fund	✓	✓	✓	✓	✓	✓	✓	✓
14	JM MidCap Fund	✓	✓	✓	✓	✓	✓	✓	✓
15	Kotak Emerging Equity Fund	✓	✓	✓	✓	✓	✓	✓	✓
16	LIC MF MidCap Fund	✓	✓	✓	X	✓	✓	✓	✓
17	Mahindra Manulife MidCap Fund	✓	✓	✓	X	✓	✓	✓	✓
18	Mirae Asset MidCap Fund	✓	✓	✓	X	✓	✓	✓	✓
19	Motilal Oswal MidCap Fund	✓	✓	✓	X	✓	✓	✓	✓
20	Nippon India Growth Fund	✓	✓	✓	✓	✓	✓	✓	✓
21	PGIM India MidCap Opportunities Fund	✓	✓	✓	X	✓	✓	✓	✓
22	Quant MidCap Fund	✓	✓	✓	✓	✓	✓	✓	✓
23	SBI Magnum MidCap Fund	✓	✓	✓	X	✓	✓	✓	✓
24	Sundaram MidCap Fund	✓	✓	✓	✓	✓	✓	✓	✓
25	Tata MidCap Growth Fund	✓	✓	✓	X	✓	✓	✓	✓
26	Taurus MidCap Fund	✓	✓	✓	✓	✓	✓	✓	✓
27	Union MidCap Fund	✓	✓	✓	X	✓	✓	✓	✓
28	UTI—MidCap Fund	✓	✓	✓	✓	✓	✓	✓	✓
29	WhiteOak Capital MidCap Fund	✓	✓	✓	✓	✓	✓	✓	✓

[1] The "X" mark in the table indicates the exclusion of the MidCap funds for the non-availability of the data.

Table 3. List of SmallCap mutual funds, part of dataset (from February to September 2024) [1].

Sl. No	SmallCap Mutual Funds	February 2024	March 2024	April 2024	May 2024	June 2024	July 2024	August 2024	September 2024
1	Aditya Birla Sun Life SmallCap Fund	✓	✓	✓	✓	✓	✓	✓	✓
2	Axis SmallCap Fund	✓	✓	✓	✓	✓	✓	✓	✓
3	BANDHAN SmallCap Fund	✓	✓	✓	X	✓	✓	✓	✓
4	BANK OF INDIA SMALLCAP FUND	✓	✓	✓	✓	✓	✓	✓	✓
5	Baroda BNP Paribas SmallCap Fund	✓	✓	✓	✓	✓	✓	✓	✓
6	Canara Robeco SmallCap Fund	✓	✓	✓	X	✓	✓	✓	✓
7	DSP SmallCap Fund	✓	✓	✓	✓	✓	✓	✓	✓
8	Edelweiss SmallCap Fund	✓	✓	✓	X	✓	✓	✓	✓
9	Franklin India Smaller Companies Fund	✓	✓	✓	✓	✓	✓	✓	✓

Table 3. *Cont.*

Sl. No	SmallCap Mutual Funds	February 2024	March 2024	April 2024	May 2024	June 2024	July 2024	August 2024	September 2024
10	HDFC SmallCap Fund	✓	✓	✓	✓	✓	✓	✓	✓
11	HSBC SmallCap Fund	✓	✓	✓	X	✓	✓	✓	✓
12	ICICI Prudential SmallCap Fund	✓	✓	✓	✓	✓	✓	✓	✓
13	Invesco India SmallCap Fund	✓	✓	✓	✓	✓	✓	✓	✓
14	ITI SmallCap Fund	✓	✓	✓	X	✓	✓	✓	✓
15	JM SmallCap Fund	✓	✓	✓	✓	✓	✓	✓	✓
16	Kotak SmallCap Fund	✓	✓	✓	X	✓	✓	✓	✓
17	LIC MF SmallCap Fund	✓	✓	✓	✓	✓	✓	✓	✓
18	Mahindra Manulife SmallCap Fund	✓	✓	✓	✓	✓	✓	✓	✓
19	Motilal Oswal SmallCap Fund	✓	✓	✓	✓	✓	✓	✓	✓
20	Nippon India SmallCap Fund	✓	✓	✓	X	✓	✓	✓	✓
21	PGIM India SmallCap Fund	✓	✓	✓	✓	✓	✓	✓	✓
22	Quant SmallCap Fund	✓	✓	✓	X	✓	✓	✓	✓
23	Quantum SmallCap Fund	✓	✓	✓	✓	✓	✓	✓	✓
24	SBI SmallCap Fund	✓	✓	✓	✓	✓	✓	✓	✓
25	Sundaram SmallCap Fund	✓	✓	✓	X	✓	✓	✓	✓
26	Tata SmallCap Fund	✓	✓	✓	✓	✓	✓	✓	✓
27	Union SmallCap Fund	✓	✓	✓	✓	✓	✓	✓	✓
28	UTI SmallCap Fund	✓	✓	✓	X	✓	✓	✓	✓

[1] The "X" mark in the table indicates the exclusion of the MidCap funds for the non-availability of the data.

Upon collecting the stress test data, a thorough data pre-processing step was conducted to ensure its quality and suitability for analysis. This involved excluding schemes which had missing values and inconsistencies within the dataset to enhance its integrity and reliability for subsequent modelling efforts. We tried not to impute values for missing values across the parameters identified. Table 4 lists the 14 parameters which were identified as features for model development for evaluation purposes. These parameters were deemed to be essential for assessing mutual fund stress levels based on their presence in the stress test template, and were subsequently used as features in the modelling process.

Table 4. The 14 parameters as features for model development.

Sl. No	Independent Variables	Description
1	AUM (INR in crores)	Asset Under Management in crores of INR (1 crore equals 10 million).
2	Liability-side Top 10 investor (%)	Indicates % of AUM held by top 10 investors of the scheme.
3	Asset-side (AUM held in) LargeCap (%)	Indicates % of scheme AUM invested in LargeCap, MidCap, and SmallCap securities, and % held in cash.
4	Asset-side (AUM held in) MidCap (%)	
5	Asset-side (AUM held in) SmallCap (%)	
6	Asset-side (AUM held in) cash (%)	
7	Portfolio annualized standard deviation (%)	Standard deviation indicates how widely a stock or portfolio's returns varies from its mean over a given period. For each incremental standard deviation, there is an increasing level of reliability.
8	Benchmark annualized standard deviation (%)	

Table 4. *Cont.*

Sl. No	Independent Variables	Description
9	Portfolio beta	Beta is a measure of volatility—or systemic risk—of a security or portfolio compared to the market (usually the broad market index such as BSE-500 or NSE-500). Stocks with betas higher than 1.0 can be interpreted as more volatile than the broad market index.
10	Portfolio trailing 12 m PE	The price to earnings (P/E) ratio is one of the most widely used valuation methods, as it accounts for a company's actual earnings instead of projected earnings. The P/E ratio indicates how much an investor is willing to pay for one unit of earnings for that company. For a given company, whether the value of the current P/E is suitable depends on various factors including sector, growth prospects, business cycle, etc.
11	Benchmark PE trailing 12 m PE	
12	Benchmark PE trailing 12 m PE 1 year ago	
13	Benchmark PE trailing 12 m PE 2 year ago	
14	Portfolio turnover ratio (%)	Portfolio turnover is a measure of how frequently assets within a mutual fund scheme are bought and sold by the fund manager over a given period. Portfolio turnover is calculated by taking either the total amount of new securities purchased or the number of securities sold (whichever is less) over a particular period, divided by the total net asset value (NAV) of the fund. The measurement is usually reported for a 12-month period. For example, a 5% portfolio turnover ratio suggests that 5% of the portfolio holdings changed over a one-year period.

The stress test pro-rata liquidation variable for the 50% portfolio and 25% portfolio were considered separately for the building models, which were binned based on the categorization shown in Table 5. Separate models were built for the stress test with the 50% portfolio and 25% portfolio for each dataset across eight months separately, and they were evaluated for their predictive powers.

Table 5. Dependent variables for stress test.

Dependent Variable	Binning Categorization
Stress test pro-rata liquidation after removing bottom 20% of portfolio based on scrip liquidity (considering 10% PV with 3x volumes) 50% portfolio	Stress level $\geq$ 7 days = high stress Stress level < 7 days = low stress
Stress test pro-rata liquidation after removing bottom 20% of portfolio based on scrip liquidity (considering 10% PV with 3x volumes) 25% portfolio	

For data exclusion criteria, due to potential data incompleteness or inconsistency, a few companies were excluded from the modelling process to ensure the robustness and reliability of the analysis. This step was crucial for maintaining the integrity of the dataset and mitigating the risk of bias in the modelling results. The companies excluded from the dataset for non-availability of data with respect to a few variables is also shown in Tables 2 and 3.

For the response variable, binning was conducted by considering a stress level of 7 days and above as indicating high-stress companies.[2] Thus, companies were categorized into two levels, namely high-stress- and low-stress-level companies, across all of the months. Table 6 shows the summary of companies which were further categorized for between 50% and 25% portfolio liquidation from February to September 2024.

Table 6. Companies categorized based on stress levels (February–September 2024).

		Stress Test Pro-Rata Liquidation @ 50% Portfolio		Stress Test Pro-Rata Liquidation @ 25% Portfolio	
		Companies with Low Stress Levels	Companies with High Stress Levels	Companies with Low Stress Levels	Companies with High Stress Levels
February 2024	MidCap	19	8	23	4
	SmallCap	8	13	13	8

Table 6. *Cont.*

		Stress Test Pro-Rata Liquidation @ 50% Portfolio		Stress Test Pro-Rata Liquidation @ 25% Portfolio	
		Companies with Low Stress Levels	Companies with High Stress Levels	Companies with Low Stress Levels	Companies with High Stress Levels
March 2024	MidCap	19	8	23	4
	SmallCap	8	13	13	8
April 2024	MidCap	20	5	22	3
	SmallCap	8	13	13	8
May 2024	MidCap	7	2	8	1
	SmallCap	4	5	6	3
June 2024	MidCap	23	6	26	3
	SmallCap	16	12	20	8
July 2024	MidCap	22	7	26	3
	SmallCap	16	12	20	8
August 2024	MidCap	21	8	26	3
	SmallCap	17	11	20	8
September 2024	MidCap	20	9	26	3
	SmallCap	16	13	21	8

3. Research Methodology

This study investigates the need for predicting the mutual fund stress levels based on the 14 parameters which were identified as features for model development and for evaluation purposes. All of the variables were standardized before using them in the model building. To build the model, data for eight months from February 2024 to September 2024 were obtained, and an Artificial Neural Network (ANN) method was proposed for prediction. We used Artificial Neural Networks (ANNs) over other machine learning methods is due to their ability to analyze the impact of dynamic interrelationships among the 14 variables on the stress level, even when the information about the system was not detailed. The 14 parameters considered for building the classification model are complicated, and complex relationships can be built (Alzubaidi et al. 2021). ANNs are the most preferred method to define such complex and complicated relations, and they have the capability to establish relationships between the parameters considered and output desired in our study over other machine learning methods (Du et al. 2019; Degadwala and Vyas 2024). In recent years, we have observed that ANNs have been applied to various problems such as prediction, optimization, control systems, and many more, which can help in decision making (D'Amour et al. 2022). In our study, the main goal of using the ANN is that it is independent to the statistical distribution of the parameters considered. In this study, we tried to build an ANN consisting of between three layers and five layers. The first layer/input layer consisted of 14 parameters, which were the input variables. The middle layer was used in modelling the complex relationships in the study. Different numbers of neurons were used in the layers to model the complexity and evaluation of the problem (Harvey and Liu 2018). As observed in Equation (1), the weights connecting the Zh hidden layer with the X_j input layer is labelled as W_{ij}. Each node in the hidden layer calculates the weighted sum of the neurons in the input layer.

$$Input_j^s = \sum w_{kj} x_k^i \quad (1)$$

Outputs corresponding to these hidden layers are obtained as a result of implementing the activation function or the transfer function. The backpropagation method was used as the learning algorithm in the ANN, which initially starts with random weights. The network "learns" by gradually adjusting its weights until it can produce the target outputs specified for the 14 parameters considered in the study.

The calculation of the error in the network was carried out using Equation (2):

$$E = \frac{1}{2}\sum_j \left(t_j - O_j\right)^2 \tag{2}$$

where t_j and O_j are the actual and desired values of unit j in the output layer. The weights are updated depending on the delta rule of learning, as shown in Equation (3):

$$\Delta w_{ij} = \eta \delta_i o_i \tag{3}$$

where $\eta > 0$ is the learning rate, δ_i is a correction term, and o_i is the output of unit i in the previous layer. We observe that the correction term is proportional to the output error. In the backpropagation algorithm, the correction term is calculated using the gradient descent method, resulting in the following expression for the delta term of an output unit:

$$\delta_i = \left(\partial E / \partial o_j\right)\left(\partial o_j / \partial I_j\right) = \left(t_j - o_j^{out}\right) o_j \left(1 - o_j\right) \tag{4}$$

Thus, the correction term for the hidden nodes is calculated applying the recursive formula in Equation (5):

$$\delta_j = o_j\left(1 - o_j\right)\sum_k \delta_k w_{kj} \tag{5}$$

It is often also observed that, if a momentum term is added to the learning rule, as given in Equation (6), it can help in enhancing the performance and also the stability in the training process:

$$\Delta w_{ij} = \eta \delta_i O_i + \mu \Delta w_{ij}^{prev} \tag{6}$$

where we can observe that $0 < \mu < 1$ is a constant called momentum and the term w_{ij}^{prev} is the adjustment.

When the difference between the desired outputs and the actual outputs reaches an acceptable threshold, the process is complete. If not, the weights are adjusted to minimize the gap between the target and the actual values.

Thus, in the neural network built, each hidden layer consists of multiple nodes (or neurons), each with its own activation function, which helps introduce non-linearity to the model. The activation type of each node is *sigmoidal in nature.* Thus, the sigmoid function squashes input values to a range between 0 and 1. Thus, to build a classification-based model, the neural network was utilized with the sigmoid as the step function/activation function. For this study, the neural networks had an input layer consisting of nodes which accept the 14 predictor values in our study, and successive layers of nodes are to receive input from the previous layers (Bergstra and Bengio 2012; Hastie et al. 2009). Various configurations of neural networks were explored, including models with one, two, and three hidden layers, with the number of nodes ranging from 2 to 10. This approach allowed for flexibility and adaptability in capturing the underlying patterns and relationships within the dataset, ultimately facilitating accurate predictions of mutual fund stress levels (Chen et al. 2020; Gu et al. 2020). For the model evaluation, the trained neural network models were evaluated using appropriate performance metrics on validation models consisting of 20% as the holdout proportion. The models were evaluated using training and validation models using performance measures such as total accuracy, sensitivity, specificity, F-score, etc. Some of the important measures are mentioned below (Crone et al. 2011; Hyndman and Koehler 2006; Makridakis et al. 2019). Sensitivity measures the ability of a model to classify the observation as positive given it was positive in nature. It is given by the following formula:

$$\text{Sensitivity/True Positive Rate} = \frac{\text{True Positive (TP)}}{\text{True Positive (TP)} + \text{False Negative (FN)}} \tag{7}$$

Specificity, on the other hand, measures the ability of a model to classify the observation as negative, given that it was negative in nature. It is given by the following formula:

$$\text{Specificity} = (\text{True Negative Rate}) = \frac{\text{True Negative (TN)}}{\text{True Negative (TN)} + \text{False Positive (FP)}} \tag{8}$$

Precision measures the accuracy of positives classified using the model, and is given by the following formula:

$$\text{Precision} = \frac{\text{True Positive (TP)}}{\text{True Positive (TP)} + \text{False Positive (FP)}} \tag{9}$$

F-score/F-Measure is used in binary logistic regression models that combine both precision and recall, and is given as follows:

$$\text{F-score} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \tag{10}$$

Finally, encompassing all of the measures, we look into the misclassification rate, which is the proportion of incorrect predictions (both false positives and false negatives) to the total number of predictions. It is given as follows:

$$\text{Misclassification Rate} = \frac{\text{FP} + \text{FN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} = 1 - \text{Total Accuracy} \tag{11}$$

As we know, the total accuracy and misclassification rate are inversely related. As accuracy increases, the misclassification rate decreases, and vice versa.

For the overall examination of the results, metrics were compared between training and validation datasets. A model can achieve high accuracy on the training set, but may perform poorly on the validation set due to overfitting. Similarly, if the model achieves low accuracy on the training set but performs well on the validation set, this is an indication of underfitting (Srivastava et al. 2014). Thus, inferences were drawn based on both training and validation performance metrics to ensure that the model generalizes well. Since the launch of AFMI datasets, this is the first time any research paper has investigated modelling the stress level of mutual funds using deep learning models. For each architecture, the datasets for training and validation were in the ratio 80:20, chosen randomly for the period from February 2024 to September 2024, respectively. For the analysis, R-programming and SAS JMP software programs (R- 4.4.2 version JMP Pro 18) were used.

4. Data Analysis and Interpretation

For each month, and with response variables having either 50% pro-rata liquidation or 25% pro-rata liquidation, ANNs with different architectures were used, and each model was formed as follows:

a. Model 1: ANN with one hidden layer with two nodes, one input layer with fourteen variables, and an output layer with one variable which is categorical in nature.
b. Model 2: ANN with one hidden layer with three nodes, one input layer with fourteen variables, and an output layer with one variable which is categorical in nature.
c. Model 3: ANN with one hidden layer with nodes ranging from four to ten nodes, one input layer with fourteen variables, and an output layer with one variable which is categorical in nature (only the best model based on performance metrics in training and validation is shown).

d. Model 4: ANN with two hidden layers with two nodes each for a layer, one input layer with fourteen variables, and an output layer with one variable which is categorical in nature.
e. Model 5: ANN with two hidden layers with three nodes each for a layer, one input layer with fourteen variables, and an output layer with one variable which is categorical in nature.
f. Model 6: ANN with two hidden layers with nodes ranging from four to ten for each layer, one input layer with fourteen variables, and an output layer with one variable which is categorical in nature (only the best model based on performance metrics in training and validation is shown).

As mentioned before, the activation function used between the input layer and the hidden layer, as well as between the hidden layer and the output layer, is sigmoidal function. The learning rate and momentum rate are taken as 0.5. The operation is completed in 1000 iteration steps. The performance measures obtained for the training and validation period for each month were tabulated separately.

The structure of the ANN proposed for the months of February 2024 using six models is shown below in Figures 1–6.

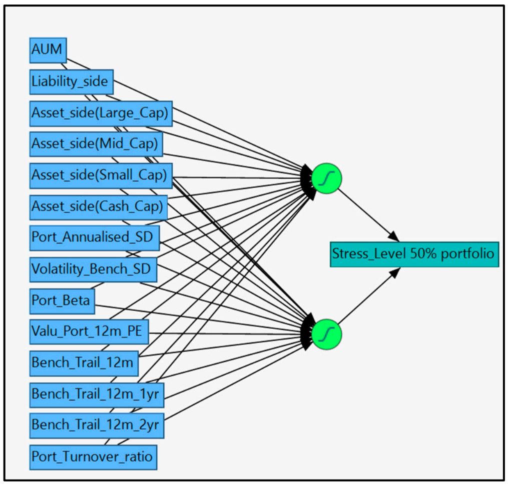

Figure 1. Model 1 depicting ANN with one hidden layer and two nodes for February 2024.

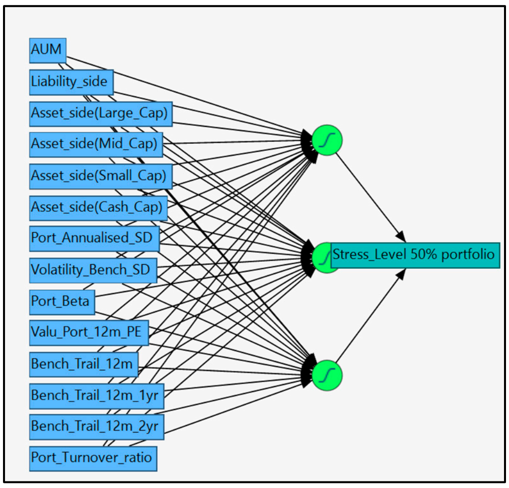

Figure 2. Model 2 presents ANN with one hidden layer and three nodes for February 2024.

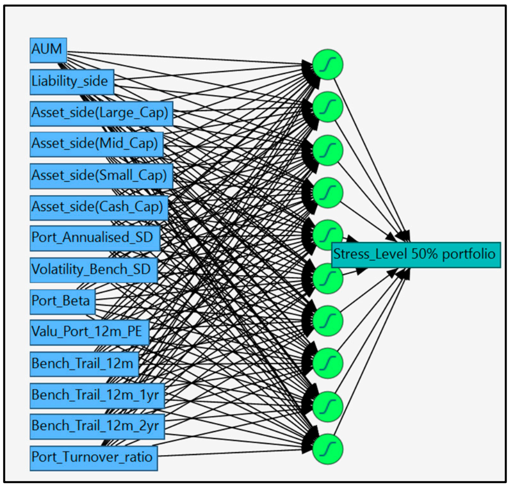

Figure 3. Model 3 depicts ANN with many nodes in the hidden layer for February 2024.

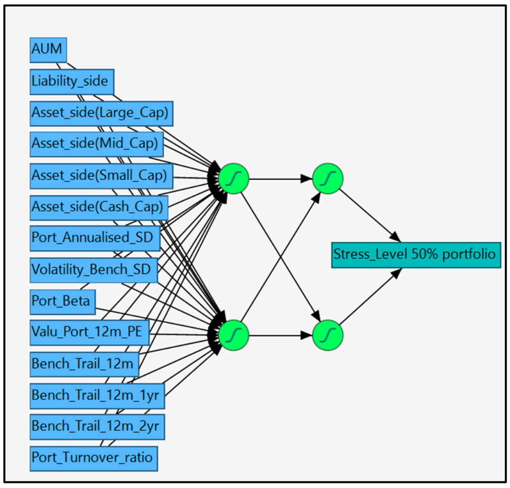

Figure 4. Model 4 presents ANN with two hidden layer with two nodes each for February 2024.

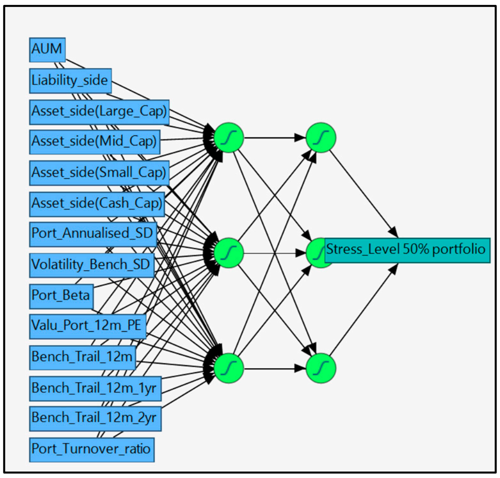

Figure 5. Model 5 presents ANN with two hidden layer with three nodes each for February 2024.

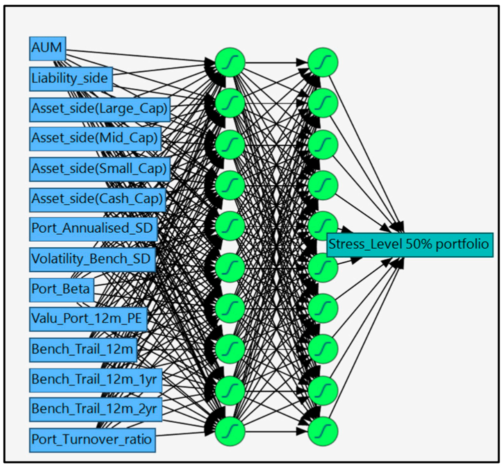

Figure 6. Model 6 presents ANN with multiple nodes for two hidden layer for February 2024.

Initially, as shown in Figures 7–9, the models that had estimates with a hidden layer varying from one to three and with varying numbers of nodes are presented to predict the pro-rata basis liquidation with the stress level at 50% portfolio for the MidCap funds for February 2024. The result of the analysis is shown in Table 7:

(a) Model building for MidCap funds for February 2024 with pro-rata basis liquidation of 50% portfolio.

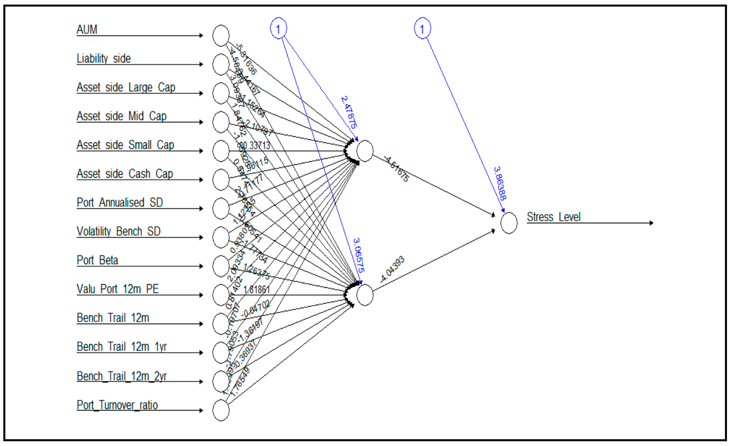

Figure 7. Model −1 for February 2024, with estimates.

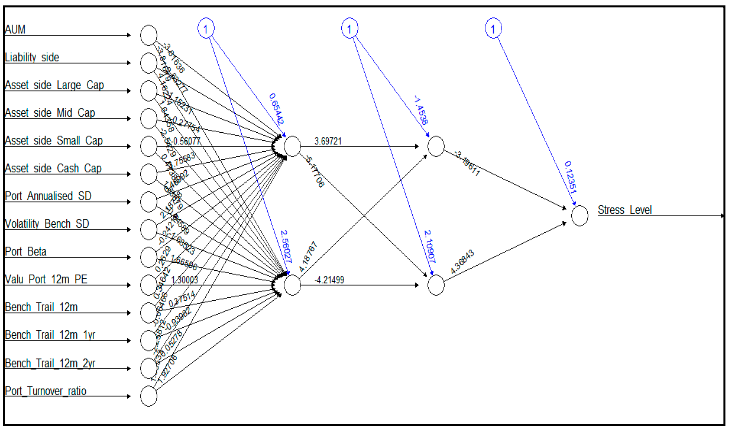

Figure 8. Model −4 for February 2024, with estimates.

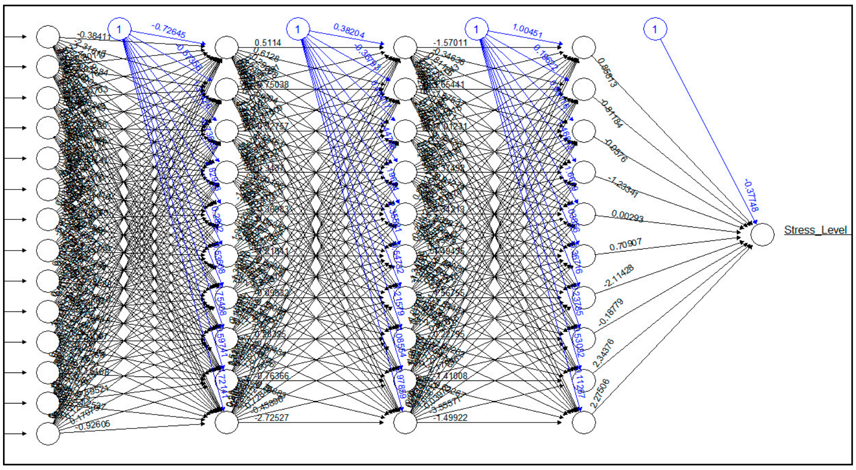

Figure 9. Model −6 for February 2024, with estimates.

Table 7. Performance metrics of ANN models for MidCap funds during February 2024 (with pro-rata basis liquidation of 50% portfolio).

Model	Accuracy	No Information Rate	Kappa	Mcnemar's Test *p*-Value	Sensitivity	Specificity
1 Hidden layer with 2 nodes	0.8	0.8	0	0.073	0.0	1.0
1 Hidden layer with 3 nodes	1.0	0.64	1	NA	1.0	1.0
2 Hidden layer with 2 nodes	0.96	0.64	0.911	1.00	1.0	0.89
2 Hidden layer with 3 nodes	0.72	0.72	0	0.023	1.0	0.0
2 Hidden layer with 10 nodes	0.72	0.72	0	0.023	1.0	0.0
3 Hidden layer with 10 nodes	0.72	0.72	0	0.023	1.0	0.0

In Table 7, consider the results shown in first row, which depicts the results for Model 1 with one hidden layer and two nodes for the dataset. We observe that, while the model demonstrates high sensitivity in correctly identifying instances of low stress levels, it suffers from low specificity and overall poor performance in accurately predicting stress levels. The accuracy of the model is calculated to be 0.8, indicating that it correctly classified 80% of the instances in the dataset. Upon splitting the dataset, 20 observations fall into training and 5 observations into test datasets. The performance metrics of Model 1 are depicted in Table 8.

Table 8. Performance metrics of Model 1 for MidCap funds during February 2024 (with pro-rata basis liquidation of 50% portfolio).

Confusion Matrix for Training Dataset			Confusion Matrix for Validation Dataset		
Actual	**Predicted Count**		**Actual**	**Predicted Count**	
Stress_Level 50% portfolio	0	1	Stress_Level 50% portfolio	0	1
0	14	0	0	4	0
1	0	6	1	0	1
Misclassification rate	0.00		Misclassification rate	0.00	

As observed, the sensitivity of the model, also known as the true positive rate, is 100%, with all 14 observations and 4 observations in the training and test data being correctly classified. The specificity of the model, which measures the true negative rate, is also 100%, with 6 observations and 1 observation in the training and test dataset being correctly classified. The misclassification rate is 0.00, indicating that the model correctly identified all instances correctly with total accuracy of 100%.

In order to compare the obtained results across various models of ANN in the training and validation datasets for the time period considered at different pro-rata basis liquidation rates, total accuracy performance metrics were tabulated and compared between the training and validation datasets across all combinations. The results are summarized in Table 9 for MidCap funds and in Table 10 for SmallCap funds, respectively. As observed, the performance metrics offer valuable insights into the models' effectiveness in predicting the liquidation strategies for different types of funds and time periods. Across all scenarios, the best-performing NN model consistently achieved perfect accuracy, indicating that it correctly predicts all instances in the dataset. This exceptional accuracy underscores the effectiveness of the model in capturing the underlying patterns and relationships in the data. Furthermore, the models consistently outperform the no information rate, which serves as a baseline performance metric, indicating that the models provide substantial value beyond random guessing. The high Kappa value of 1 for all scenarios suggests a strong agreement between the model's predictions and the actual outcomes, correcting for agreement occurring by chance. This indicates robust performance across different liquidation strategies and fund types. However, the consistent high total accuracy suggest that the performance of the best NN model remains stable and reliable. Moreover, the sensitivity and specificity metrics indicate that the model performs well in correctly identifying both positive and negative instances, respectively.

Table 9. Total accuracy of ANN across various architectures (Model 1 to Model 6) across training and validation datasets from February 2024 to September 2024 for MidCap.

		Model 1		**Model 2**		**Model 3**		**Model 4**		**Model 5**		**Model 6**	
Year		**Total Accuracy**		**Total Accuracy**		**Total Accuracy**		**Total Accuracy**		**Total Accuracy**		**Total Accuracy**	
		Training	**Validation**	**Training**	**Validation**	**Training**	**Validation**	**Training**	**Validation**	**Training**	**Validation**	**Training**	**Validation**
February 2024	STPRL@ 50% portfolio	1.00	1.00	1.00	1.00	1.00	1.00	**0.90**	**1.00**	**0.90**	**0.80**	**1.00**	**0.80**
	STPRL@ 25% portfolio	1.00	1.00	**0.70**	**1.00**	0.95	1.00	1.00	1.00	**0.80**	**1.00**	**0.80**	**1.00**
March 2024	STPRL@ 50% portfolio	1.00	1.00	1.00	1.00	1.00	1.00	**0.95**	**1.00**	1.00	1.00	1.00	1.00
	STPRL@ 25% portfolio	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
April 2024	STPRL@ 50% portfolio	1.00	0.80	**1.00**	**0.80**	**1.00**	**0.80**	**0.85**	**0.60**	**0.70**	**1.00**	**0.65**	**1.00**
	STPRL@ 25% portfolio	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.80	1.00	1.00	1.00	1.00
May 2024	STPRL@ 50% portfolio	0.86	**0.50**	**0.86**	**1.00**	0.57	1.00	**0.71**	**1.00**	**0.71**	**0.50**	**0.30**	**1.00**
	STPRL@ 25% portfolio	0.71	1.00	1.00	1.00	1.00	1.00	**1.00**	**0.50**	**1.00**	**0.50**	1.00	1.00
June 2024	STPRL@ 50% portfolio	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	STPRL@ 25% portfolio	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
July 2024	STPRL@ 50% portfolio	0.95	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	STPRL@ 25% portfolio	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
August 2024	STPRL@ 50% portfolio	**0.57**	**0.60**	1.00	1.00	**0.91**	**0.40**	1.00	1.00	**0.38**	**0.40**	**0.91**	**0.80**
	STPRL@ 25% portfolio	0.86	1.00	1.00	1.00	1.00	1.00	**0.86**	**1.00**	1.00	1.00	1.00	1.00
September 2024	STPRL@ 50% portfolio	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	STPRL@ 25% portfolio	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Table 10. Total Accuracy of ANN across various architectures (Model 1 to Model 6) across training and validation datasets from February 2024 to September 2024 for SmallCap.

Year		Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
		Total Accuracy		Total Accuracy		Total Accuracy		Total Accuracy		Total Accuracy		Total Accuracy	
		Training	Validation	Training	Validation	Training	Validation	Training	Validation	Training	Validation	Training	Validation
February 2024	STPRL@ 50% portfolio	**0.88**	**1.00**	**0.35**	**1.00**	1.00	1.00	1.00	1.00	**1.00**	**0.75**	1.00	1.00
	STPRL@ 25% portfolio	**0.53**	**0.75**	**0.53**	**1.00**	**0.47**	**1.00**	0.71	0.75	**0.64**	**0.50**	**0.29**	**0.75**
March 2024	STPRL@ 50% portfolio	**1.00**	**0.75**	**1.00**	**0.75**	**1.00**	**0.75**	1.00	0.75	1.00	0.75	1.00	1.00
	STPRL@ 25% portfolio	1.00	1.00	1.00	1.00	**0.44**	**1.00**	1.00	1.00	1.00	1.00	1.00	1.00
April 2024	STPRL@ 50% portfolio	**0.35**	**0.75**	1.00	1.00	1.00	1.00	**0.88**	**0.75**	**0.53**	**1.00**	**0.94**	**1.00**
	STPRL@ 25% portfolio	**0.94**	**0.75**	1.00	1.00	**0.59**	**1.00**	**0.53**	**1.00**	1.00	1.00	**0.71**	**1.00**
May 2024	STPRL@ 50% portfolio	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	STPRL@ 25% portfolio	1.00	1.00	1.00	1.00	**0.72**	**1.00**	**0.57**	**1.00**	**0.43**	**0.50**	**0.71**	**1.00**
June 2024	STPRL@ 50% portfolio	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	STPRL@ 25% portfolio	1.00	1.00	**1.00**	**0.75**	**0.53**	**1.00**	**0.88**	**1.00**	1.00	1.00	1.00	1.00
July 2024	STPRL@ 50% portfolio	1.00	1.00	1.00	1.00	**0.62**	**1.00**	1.00	1.00	1.00	1.00	1.00	1.00
	STPRL@ 25% portfolio	1.00	1.00	**0.67**	**0.75**	**0.61**	**0.75**	1.00	1.00	**0.56**	**0.75**	**0.22**	**0.75**
August 2024	STPRL@ 50% portfolio	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	STPRL@ 25% portfolio	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	**0.78**	**1.00**	1.00	1.00
September 2024	STPRL@ 50% portfolio	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	STPRL@ 25% portfolio	**0.44**	**1.00**	**0.66**	**1.00**	**0.55**	**0.75**	**0.55**	**1.00**	**0.61**	**1.00**	**0.72**	**1.00**

The perfect sensitivity and specificity scores further validate the model's ability to accurately predict the liquidation strategies for both MidCap and SmallCap funds across different time periods and portfolio liquidation percentages. Overall, the results demonstrate the effectiveness of the NN model in predicting optimal liquidation strategies for MidCap and SmallCap funds, highlighting its potential utility in financial decision-making processes.

5. Conclusions and Scope for Future Research

The recent introduction of innovative methodologies for evaluating mutual fund performance and risk in India, exemplified by the Association of Mutual Funds of India's (AMFI) "Stress Test" initiative, marks a significant transformation in the investment landscape. This initiative, supported by SEBI's outlined methodology, aims to assess the stress levels in MidCap and SmallCap mutual funds by simulating scenarios of significant redemption requests. The proactive approach taken by AMFI and SEBI reflects a commitment to enhancing transparency and accountability within the mutual fund industry, ultimately empowering investors with deeper insights into the resilience of their investment portfolios. The results obtained from the analysis highlights the effectiveness of neural network models in predicting optimal liquidation strategies for MidCap and SmallCap funds under different scenarios. The consistently high accuracy, Kappa value, sensitivity, and specificity metrics underscore the reliability and robustness of these models in assessing fund performance and risk.

In conclusion, the integration of innovative methodologies such as stress testing into mutual fund evaluation frameworks represents a positive step towards bolstering investor confidence and promoting informed decision making. By providing insights into how funds perform under stress scenarios, investors can better understand the potential risks associated with their investments and make more informed choices.

Moving forward, there are several suggestions and avenues for future research. Firstly, the ongoing monitoring and refinement of stress testing methodologies will be essential to ensure their effectiveness in capturing evolving market dynamics. Additionally, exploring the application of advanced machine learning techniques beyond neural networks, such as ensemble methods or deep learning architectures, could further enhance the accuracy and predictive power of fund evaluation models. Furthermore, conducting comprehensive studies to evaluate the impact of stress testing initiatives on investor behaviour, market stability, and fund performance over the long term would provide valuable insights for industry stakeholders and regulators. Future research could investigate the behavioural patterns of retail investors when they are presented with risk-related metrics such as stress test results and liquidity parameters. Future research could delve into more sophisticated deep learning architectures to refine the prediction of stress parameters. Studies could test ensemble learning techniques or hybrid models that combine neural networks with other statistical methods for potentially higher accuracy.

Overall, the introduction of stress testing initiatives represents a significant milestone in the evolution of mutual fund evaluation practises in India. By embracing innovation and adopting proactive measures to enhance transparency and accountability, the mutual fund industry can continue to foster investor trust and contribute to the development of a resilient and sustainable financial ecosystem. By leveraging advanced computational techniques, this study contributes to the ongoing discourse surrounding risk management and decision-making in the realm of mutual fund investments. The insights garnered from this research have practical implications for investors, fund managers, and regulatory bodies, facilitating more informed investment strategies and risk mitigation measures in the mutual fund industry.

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Data Availability Statement: The data is freely available in the website's dedicated section with the heading, "Disclosure of Stress Test & Liquidity Analysis in respect of MidCap & SmallCap Funds". We encourage aspirants to download it and test the models.

Conflicts of Interest: The authors declare no conflicts of interest.

Notes

1. https://www.livemint.com/mutual-fund/mid-small-cap-mutual-funds-regulators-took-these-4-steps-to-protect-investors-from-high-valuations-amfi-sebi-s-11709284068761.html, accessed on 10 March 2024.
2. In the article titled "*Revealed! No. of days Nippon India, biggest small-cap fund, will need to sell off 50% of its portfolio*", the authors emphasized that more than 3–6 days would suggest stress in the mutual fund. https://www.businesstoday.in/mutual-funds/story/revealed-no-of-days-nippon-india-biggest-small-cap-fund-will-need-to-sell-off-50-of-its-portfolio-421556-2024-03-15, accessed on 20 April 2024.

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