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Net Asset Value (NAV) Prediction using Dense Residual Models

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Abstract

Net Asset Value (NAV) has long been a key performance metric for mutual fund investors. Due to the considerable fluctuation in the NAV value, it is risky for investors to make investment decisions. As a result, accurate and reliable NAV forecasts can help investors make better decisions and profit. In this research, we have analysed and compared the NAV prediction performance of our proposed deep learning models, such as N-BEATS and NBSL, with the FLANN model in both univariate and multivariate settings for five Indian mutual funds for forecast periods of 15, 20, 45, 63, 126, and 252 days using RMSE, MAPE, and R2 as evaluation metrics. A large forecast horizon was chosen to assess the model's consistency, reliability, and accuracy. The result reveals that the N-BEATS model outperforms the

FLANN and NBSL models in the univariate setting for all datasets and all prediction horizons. In a multivariate setting, the outcome demonstrates that the N-BEATS model outperforms the FLANN model across all datasets and prediction horizons. The result also shows that, as the number of forecast days grew, our suggested models, notably N-BEATS, maintained consistency and attained the highest R2 value throughout the longest forecast duration.

Keywords: Net Asset Value; NAV prediction; Mutual Funds; N-BEATS; FLANN; LSTM.

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Introduction

Mutual funds are recognised as one of the most reliable financial investment vehicles in today's world due to their diverse and flexible structure. A mutual fund is a sort of investment vehicle in which a group of individuals aggregate their money and invest it in a wide portfolio of stocks, bonds, money market instruments, gold, and other assets. The fund manager is in charge of overseeing the whole operation to ensure that it is professional and profitable. He does preliminary research to identify the finest stocks to invest in and then closely monitors performance to maximise returns. The market value of the securities invested in determines the performance of the funds raised, which is referred to as the "Net Asset Value" (NAV). It provides us with the unit price of a mutual fund's specific scheme, making it easier for investors to buy or sell shares in that scheme. Because the market value of assets changes on a daily basis, the NAV for all mutual fund schemes varies on a daily basis. Investors examine the NAV's appreciation before making any investment choice since it reflects possible earnings.

It is perilous for investors to make investment decisions because of the significant volatility of the NAV. As a result, accurate and reliable NAV forecasting may assist investors in making informed decisions and profiting. Statistical techniques, however, find it difficult to forecast properly due to non-linear, chaotic, and missing data in financial time series. As a result, machine learning algorithms account for these anomalies and boost prediction performance (Henrique et al., 2019). In this research, we have analysed and compared the NAV prediction performance of our proposed deep learning models, such as N-BEATS and NBSL, with the FLANN model in both univariate and multivariate settings for five Indian mutual funds for forecast periods of 15, 20, 45, 63, 126, and 252 days. Furthermore, to enhance prediction performance, we have employed BSE SENSEX and MCX as independent variables in multivariate N-BEATS, NBSL, and FLANN models. The performance of the models was assessed using the three evaluation metrics: RMSE, MAPE, and R2. This paper's body of work is structured as follows: Initially, we'll examine the methodologies we employed, including N-BEATS, LSTM, and FLANN models, as well as their design. Then, we describe the datasets and their sources that were used to train and evaluate the models in our study. We'll also discuss the data preparation methods and independent variables used in our research. Then, an experimental analysis of the methodologies will be presented alongside their results. We will also evaluate the outcomes of the suggested techniques using evaluation metrics. The paper concludes with a concise discussion and recommendations for future research.

Literature Review

Using various machine learning algorithms, a lot of research has been done on predicting net asset value. (Hota et al., 2021) employed MLP, ELM, and FLANN neural network models to predict the NAV of one of India's mutual funds. In terms of anticipating NAV values, ELM beat the other two models. For NAV prediction, (Mohanty & Dash, 2021) used a Chebyshev polynomial neural network with three independent NAV sets of data. The Flower Pollination Method, a nature-inspired algorithm, was used to predict the network's regulating parameters. A comparative study with other algorithms such as PSO and DE was used to assess the effectiveness of the suggested model. The suggested model outperformed other models, according to the results. For NAV forecasting, (Rout et al., 2021) compare and contrast numerous functional link artificial neural network expansion approaches, including trignometric, chebyshev, lengendre, and power series. The potential of a relationship between each functional expansion and training factors such as learning rate, number of expansions, and so on was also studied. The models' predictions for the short- and long-term horizons were also compared, with legendre expansion being the optimum for the short-term horizon and power expansion being the optimum for the long-term horizon and convergence.

When (Hota et al., 2021) used the firefly algorithm to evaluate the weights of a functional link artificial neural network for forecasting two mutual funds in India, he discovered that the suggested FLANN model with the firefly algorithm outperformed the basic model without the firefly method when measured against the evaluation metric. (Koudjonou & Rout, 2020) conducted extensive research using three data processing techniques (MTMF, MTSF, and STSF), 2 kinds of RNN (LSTM and GRU), 2 operating modes (stateful and stateless), and 3 RNN architectures (single, stacked and bidirectional), and 3 RNN architectures (single, stacked, and bidirectional). When it comes to NAV prediction, stacked or bidirectional RNN results do not necessarily beat single RNN. The stateless GRU–MTMF model was discovered to be the most stable model for both short- and long-term forecasts. (Hota et al., 2018) used the extreme learning machine in combination with the dolphin swarm algorithm as a forecast model, with the swarm-based technique enhancing the extreme learning machine variables. It was found that the combined extreme learning machine and dolphin swarm approach beat the conventional extreme learning machine model in terms of forecast accuracy when applied to two Indian mutual fund datasets. (Majhi et al. 2021) employed a composite ensemble approach with three adaptive frameworks and compared it to models such as the adaptive moving average, the adaptive auto-regressive moving average, and FLANN, and discovered that the suggested model was more successful than the others in predicting NAV.

(Anish and Majhi, 2015, 2016) used functional link ANN to predict NAV at first, but then switched to an ensemble model combining radial basis function and functional link ANN, which proved to be superior to single individual models. In another study, (Anish and Majhi, 2015) used feedback functional link artificial neural networks to predict NAV, and it was found to be much better than functional link ANN and multilayer ANN. In 1996, back propagation neural networks were employed to forecast mutual fund NAV and compared to statistical approaches; (Chiang et al., 1996) found that neural networks outscored econometrics techniques. (Santos Junior et al., 2019) suggested a hybrid model that used the ARIMA model for linear patterns and the multi-layer perceptron and support vector regression models for non-linear patterns. This hybrid model was used to examine six convoluted time series. The suggested hybrid model outperformed single and other hybrid models employed by previous researchers. For forecasting high frequency time series, (Galicia et al., 2019) developed an ensemble model including random forest, decision tree, and gradient boosted trees. The ensemble's weights were assigned using the weighted least square approach, and the weights were modified using static and dynamic procedures. The investigation was conducted using high-frequency 10-minute data of Spanish power usage over a ten-year period. The results demonstrated that the ensembles, both static and dynamic, outperformed the individual members. In addition, the dynamic model turned out to be the most accurate.

(Priyadarshini and Babu, 2012) compared the forecasting results of the traditional multiple regression model and the artificial neural network model. For the years 2003- 2008, one of the Indian mutual funds was studied. The BSE index, NSE index, GDP, inflation, and other independent or feature variables were used in the analysis. The ANN significantly outperformed the multiple regression model, according to the results. (Priyadarshini, 2015) examined the ARIMA and ANN models' performance in forecasting the NAV price of a Sahara mutual fund. The data was collected between 2006 and 2012. The assessment criteria used to assess performance were MAE, MAPE, RMSE, and MSE. The ANN model outperformed the ARIMA model, according to the results. (Mili and Hamdi, 2013) proposed the hybrid FLANN model for data mining categorization tasks. Three different optimization algorithms were used, including GA, particle swarm, and differential evolution. The suggested model outperformed the FLANN model, according to the results. Furthermore, trignometric expansion was shown to be the most effective.

Methodology

The FLANN and the proposed N-BEATS models are described in this section.

FLANN Model

A Functional Link Artificial Neural Network (FLANN) is a single-layer model that has just one input layer, one output layer, and no hidden layer, distinguishing it from multi-layer perceptrons. The input characteristics of the FLANN model are increased by the functional expansion elements with the aid of a basis function; in our case study, the basis function is trigonometric, which facilitates the introduction of non-linearity in the dataset. It has an input layer with P features I1,......,Ip for I input variables. Each input feature Ig is now increased to a y corresponding basis function, which produces the maximum magnified input as shown in equation (1).

$$I'_g = \{f_0(I_g), f_1(I_g), \ldots\ldots\ldots\ldots, f_t(I_g)\} \tag{1}$$

Where I′g is the expanded input, f0 (.), f1 (.),…………,ft(.) is the trigonometric basis function.

For expansion, the sin and cos functions are used in the trigonometric basis function. The nth fractional sum of its Fourier series with regard to an orthogonal system is the closest estimate in the metric space of L2 for all polynomials of the nth order with respect to the system, $\omega(\vartheta)_{i=1}^{n}$. The equation (2) represents the trignometric expansion with the input feature Ig that we used in our research.

$$I'_g = \{ I_g, \sin(\pi I_g), \cos(\pi I_g), \sin(2\pi I_g), \cos(2\pi I_g), \ldots\ldots\ldots, \sin(t\pi I_g), \cos(t\pi I_g)\} \tag{2}$$

The features are directly transferred to the C nodes of the output layer following expansion using weighted linkages. The output layer nodes at the relevant nodes calculate the forecasted score for each class. Weighted sums of the expanded inputs are determined at the output layer. These predicted scores are gradually brought closer to the goal scores by adjusting the weights and minimising the error, (Law et al., 2019).

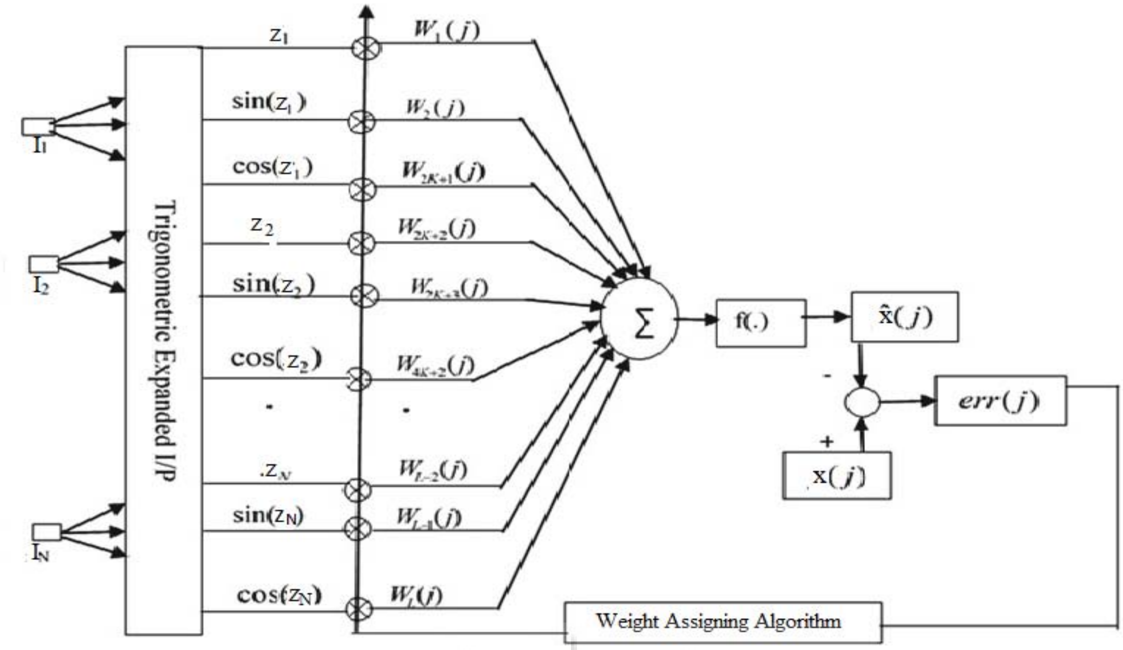

Figure 1. Basic FLANN Model Architecture (Courtesy: Hota et al., 2021)

Proposed model - N-BEATS

N-BEATS is a deep neural network algorithm that consists of two parts: blocks, which are fundamental units, and residual connections, which are skip connections. It aids in the resolution of the vanishing gradient problem, which is common in deep neural network architecture. The two fundamental units are the N dense layer with relu activation function and the gamma dense layer with a linear activation function. The gamma dense layer follows the Nth dense layer, as shown in equation (1).

For any Y^{th} unit (in block) –

$k_{y,1} = FC_{y,1}(z_y)$,

$k_{y,2}=FC_{y,2}(k_{y,1})$

$k_{y,N} = FC_{y,N}(k_{y,N-1})$ (1)

Where (ky,1 – ky,N) is the hidden layer(1st y unit – Nth y unit), zy is the intial input, FC is the fully connected layer.

Forecast and backcast are the two outputs of each block. The forward (γ_y^f) and backward (γ_y^b) expansion coefficients as shown in equation (2) and (3) are accepted by the forward (t_l^f) and backward ((t_l^b) basis layers, which provide backcast ($\hat{a}$y) and forecast output ($\hat{b}$y) as shown in equation (4) and (5).

$\gamma_y^b = Linear_y^b(k_{l,N})$ (2)

$\gamma_y^f = Linear_y^f(k_{l,N})$ (3)

Here Linear implies linear projection layer i.e.

$\gamma_y^b = w_y^b\ \mathrm{k}_{l,N}$

$\gamma_y^f = w_y^f\ \mathrm{k}_{l,N}$

$\hat{a}_y = t_l^b(\gamma_y^b)$ (Backcast) (4)

$\hat{b}_y = t_l^f(\gamma_y^f)$ (Forecast) (5)

Dual Skip Connection

Equation (6) shows how the input of unit (y-1) is subtracted from the backcast of basic block (y-1) and given to the yth unit as its input.

$a_y = a_{y-1} - \hat{a}_{y-1}$ (6)

The forecast for the yth unit is added to the forecast for the (y+1)th unit, after which the forecasts for all units are aggregated, and ultimately the overall forecast is calculated as shown in equation (7), (Oreshkin et al., 2020).

$\hat{b}_y = \sum \hat{b}y$ (7)

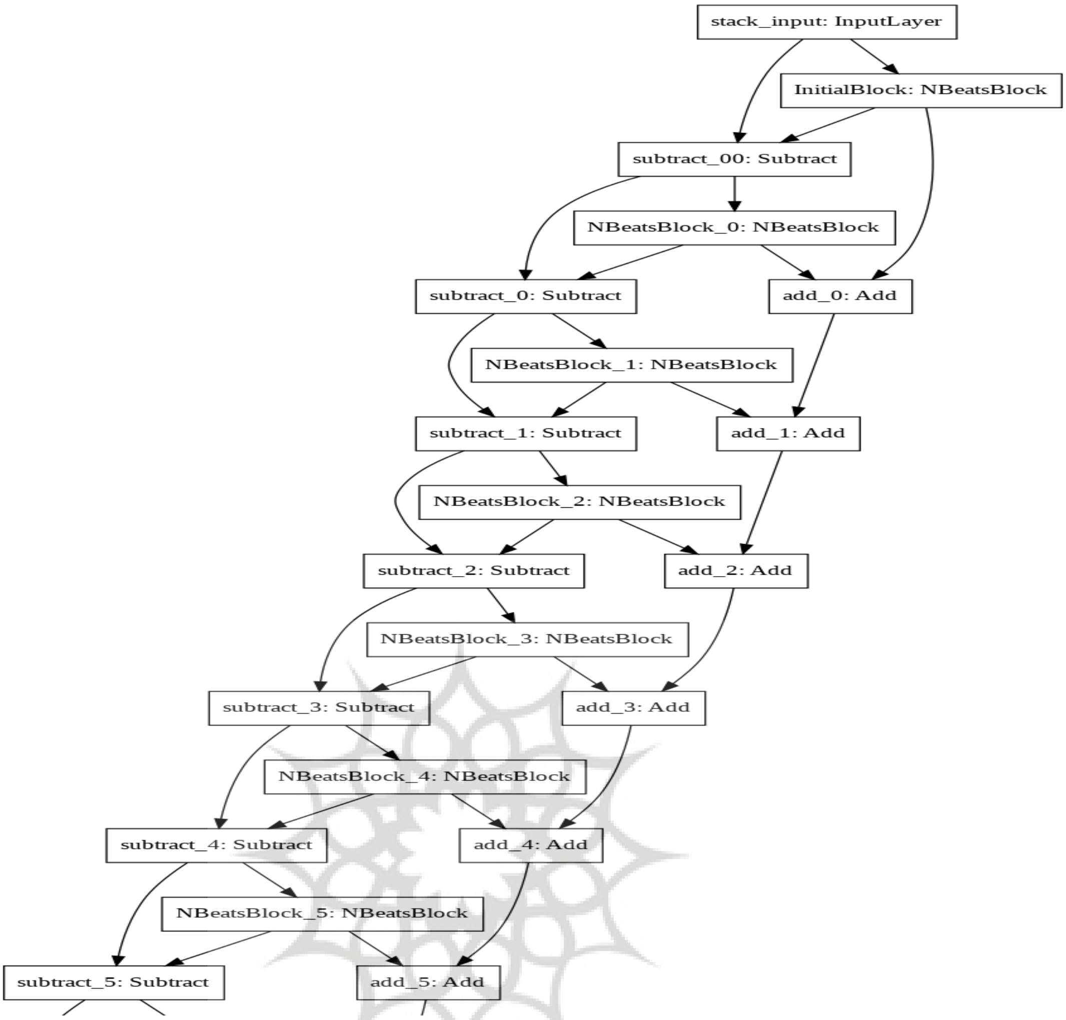

Figure 2. Simplified Architecture of N-BEATS model

Proposed model - N-BEATS stacked LSTM (NBSL)

Long Short-Term Memory (LSTM)

An advancement in recurrent neural networks (RNN) is the LSTM-based models. By allowing RNNs to store and learn long-term dependencies of inputs in their memory, LSTM models resolve the problems with RNNs like vanishing gradients and exploding gradients. Long-term retention of information is made easier with the aid of this LSTM memory extension. The capacity to choose whether to keep or discard memory information is the reason the LSTM memory is referred to as a gated cell. Important input characteristics are captured by an LSTM model, which keeps this data intact for a very long time. The weight values given to the information throughout the training stage are used to determine whether to keep or delete it. As a result, an LSTM model learns which information should be kept or deleted, (Siami-Namini et al., 2019).

An LSTM model usually has three gates: forget, input, and output.

1. Forget Gate- This gate typically uses a sigmoid function to determine what data needs to be deleted from the LSTM memory. The value of h_{t-1} and x_t is largely taken into account while making this choice. The result of this gate is f_t, a number between 0 and 1, where 1 denotes the retention of the entire value and 0 suggests totally disposing of the learnt value. The output is calculated as follows in equation (1):

$$f_t = \sigma\ (w_f\ [h_{t-1}, x_t], b_f=) \tag{1}$$

Where ft is the forget gate, σ is the sigmoid function, wf is the weight assigned to forget gate neuron, ht-1 is the output of previous (t-1) lstm block, xt is the input at current timestamp, bf is the forget gate bias.

2. Input Gate - This gate determines whether to store the new data in the LSTM memory.This gate is composed of two layers, the sigmoid layer and the tanh layer. The sigmoid layer decides which values need to be updated, and the tanh layer offers a vector of new candidate values that will be put to the LSTM memory. These two layers' outputs are calculated as shown in equation (2) and (3):

$$i_t = \sigma\ (w_i\ [h_{t-1}, x_t], b_i) \tag{2}$$
$$\widetilde{ct} = \tanh\ (w_c\ [h_{t-1}, x_t], b_c) \tag{3}$$

Where it is the input gate, σ is the sigmoid function, wi is the weight assigned to input gate neurons, ht-1 is the output of previous(t-1) lstm block, xt is the input at current timestamp, bi is the input gate bias, and $\widetilde{ct}$ is the candidate for cell state at timestamp(t).

These two layers work together to update the LSTM memory, as shown in equation (4), by multiplying the previous value (ct-1) and adding the new candidate value it*ct before utilising the forget gate layer to erase the current value.

$$c_t = f_t * c_{t-1} + i_t * c_t \tag{4}$$

Where ct is the cell state at timestamp (t), ft is the forget gate, ct-1 is the cell state at timestamp (t-1), and it is the input gate.

3. Output Gate - This gate determines which portion of the LSTM memory will contribute to the output using a sigmoid layer. A non-linear tanh function is then used to translate the values between -1 and 1. The output of a sigmoid layer is then multiplied by the outcome, (Siami-Namini et al., 2019). The output is computed as follows in equation (5):

$$o_t = \sigma\ (\ w_o[h_{t-1}, x_t], b_o) \tag{5}$$
$$h_t = o_t * \tanh(c_t)$$

Where ot is the output gate, σ is the sigmoid function, wo is the weight assigned to output gate neurons, ht-1 is the output of previous (t-1) lstm block, xt is the input at current timestamp, bo is the output gate bias, ht is the output of current timestamp (t), and ct is the cell state at timestamp (t).

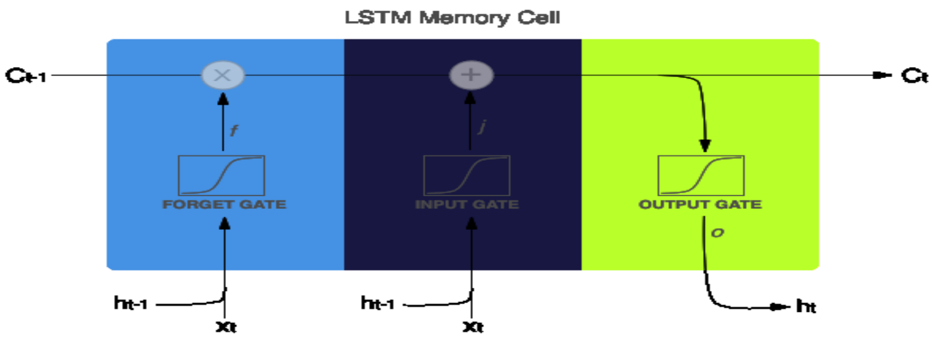

Figure 3. LSTM memory cell (Courtesy: Thakur, 2018)

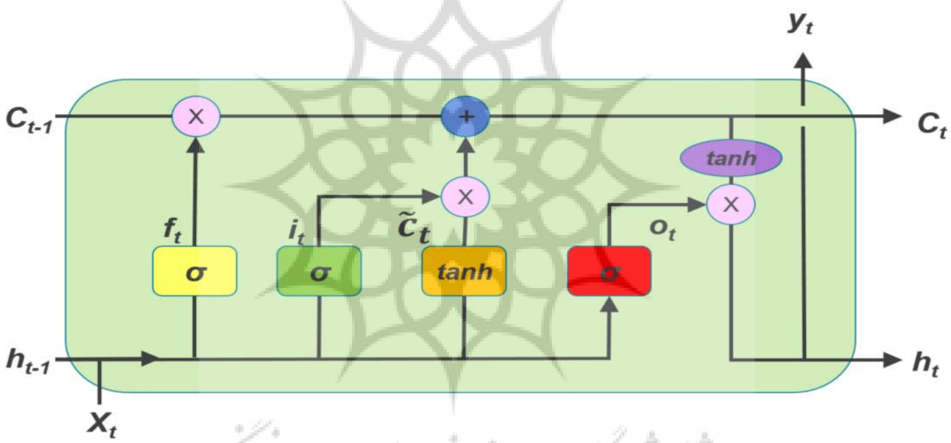

Figure 4. LSTM block at timestamp (t) (Courtesy: Thakur, 2018)

Data Representation and Preparation

The five eminent Indian equity mutual funds from which daily NAV data is obtained are: Axis Bluechip Growth Fund, Axis Midcap Growth Fund, Mirae Asset Largecap Growth Fund, SBI Smallcap Growth Fund, and UTI-Flexicap IDCW Fund for the period 1 January 2017 to 31 December 2021. The mutual funds chosen are all equity-based, high-performing schemes. We also used data from two stock indices, the BSE Sensex and the MCX, as independent variables for multivariate analysis. Our data comes from the websites of the Association of Mutual Funds in India (AMFI), the Bombay Stock Exchange (BSE), and the Multi Commodity Exchange (MCX). A quick overview of our data and its characteristics can be found in table 1. During data preparation, we performed the normalisation technique to move and rescale the NAV data, resulting in data that varied from 0 to 1. Data was imputed for missing values using the predictive mean matching (PMM) method. In our study, 80 percent of the data was used to train the models, while the remaining 20 percent was applied to test the model's performance. Table 2 shows descriptive statistics for all of the datasets included in our study. The correlation between the chosen independent variables, the BSE Sensex and the MCX, and all of the datasets for the multivariate setting is shown in Table 3.

Table 1. Data Description

Mutal fund's Name	Data Period	Total number of Initial samples	Total number of Samples after Data Pre-processing	Number of training Samples	Number of testing Samples
Axis Midcap Fund - Growth	01-01-2017 to 31-12-2021	1289	1282	1025	257
Axis Bluechip Fund- Growth	01-01-2017 to 31-12-2021	1289	1282	1025	257
Mirae Asset Large Cap Fund- Growth	01-01-2017 to 31-12-2021	1290	1283	1026	257
SBI Small Cap Fund- Growth	01-01-2017 to 31-12-2021	1289	1282	1025	257
UTI Flexicap Fund-IDCW	01-01-2017 to 31-12-2021	1288	1281	1024	257
BSE Sensex	01-01-2017 to 31-12-2021	1239	1239	Matches the training sample number for the respective NAV dataset	257
MCX	01-01-2017 to 31-12-2021	38581	1284	Matches the training sample number for the respective NAV dataset	257

Table 2. Descriptive Statistics

	Axis Bluechip	Axis Midcap	Mirae Asset LargeCap	SBI SmallCap	UTI Flexicap	BSE Sensex	MCX
Median	28.29	35.75	51.52	56.36	102.88	37145.45	2777226
Mean	30.17	40.22	55.37	63.27	112.27	39294.84	2842348
SE.mean	0.2	0.32	0.35	0.55	0.76	236.99	24571.77
CI.mean(0.95)	0.39	0.63	0.68	1.08	1.49	464.95	48205.25
Variance	50.65	134.44	154.37	389.56	740.3	69587633	7.75E+11
Std.deviation	7.12	11.59	12.42	19.74	27.21	8341.92	880478.8
Coef. of Variation	0.24	0.29	0.22	0.31	0.24	0.21	0.31

Table 3. Spearman Correlation between independent variables, the BSE Sensex and the MCX, with all of the datasets

	Axis Midcap	Axis Bluechip	Mirae Asset	SBI Smallcap	UTI
BSE	0.90924	0.913725	0.901307	0.743942	0.862448
MCX	0.551496	0.576173	0.480714	0.328143	0.408785

Results

Experimental Set-up

We compared and analysed the prediction performance of the proposed univariate N-BEATS and N-BEATS stacking LSTM models with that of the univariate FLANN model in order to forecast NAV. The multivariate FLANN model's prediction performance is compared and analysed together with that of the proposed multivariate N-BEATS and NBSL models. Table 4a–4d shows the hyperparameters tuned for the proposed univariate and multivariate N-BEATS and NBSL models. Hyperparameters like epochs, neurons, window size, and horizon period are the same for both the univariate and multivariate N-BEATS models. However, the number of fully connected layers and the number of stacks are different for both models. The hyperparameter settings for the univariate and multivariate NBSL models are the same.

Table 4a. Hyperparameters for Univariate N-BEATS

Hyperparameters	Axis Midcap	Axis Bluechip	Mirae Asset LargeCap	SBI SmallCap	UTI Flexicap
Epochs	5000	5000	5000	5000	5000
No. of Neurons	512	512	512	512	512
Window size	7	7	7	7	7
Horizon period	1	1	1	1	1
No. of fully connected layers	6	4	6	4	4
No. of Stack	39	30	33	50	43

Table 4b. Hyperparameters for Univariate NBSL

Hyperparameters	Axis Midcap	Axis Bluechip	Mirae Asset LargeCap	SBI SmallCap	UTI Flexicap
Epochs	5000	5000	5000	5000	5000
No. of Neurons	128	128	128	128	128
Window size	7	7	7	7	7
Horizon period	1	1	1	1	1
LSTM stack layer	4	4	4	4	4
No. of Stack	10	10	10	10	10

Table 4c. Hyperparameters for Multivariate N-BEATS

Hyperparameters	Axis Midcap	Axis Bluechip	Mirae Asset LargeCap	SBI SmallCap	UTI Flexicap
Epochs	5000	5000	5000	5000	5000
No. of Neurons	512	512	512	512	512
Window size	7	7	7	7	7
Horizon period	1	1	1	1	1
No. of fully connected layers	4	6	6	6	6
No. of Stack	37	53	53	53	45

Table 4d. Hyperparameters for Multivariate NBSL

Hyperparameters	Axis Midcap	Axis Bluechip	Mirae Asset LargeCap	SBI SmallCap	UTI Flexicap
Epochs	5000	5000	5000	5000	5000
No. of Neurons	128	128	128	128	128
Window size	7	7	7	7	7
Horizon period	1	1	1	1	1
LSTM stack layer	4	4	4	4	4
No. of Stack	10	10	10	10	10

The models are subjected to all of the training patterns in order, and the resulting error values are recorded. Each set of sequences has its mean squared error (MSE) calculated. The training process is terminated when the mean squared error, as described in, reaches its lowest possible value and does not fall any further. Following the training phase, the models' prediction performance is assessed using the remaining 20 percent of the test data. The mean absolute percentage error (MAPE), root of the mean squared error (RMSE), and coefficient of determination (R2) are used to evaluate and analyse prediction accuracy.

The square root of the Mean Squared Error (MSE) is called the Root Mean Squared Error (RMSE) as shown in equation (1). It's a metric for determining the residuals' standard deviation.

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{N}\sum_{p=1}^{N}\left(f_i - \hat{f}\right)^2} \quad (1)$$

Where f_i is the actual value and, $\hat{f}$ is the forecast value.

We can measure the accuracy using MAPE by looking at the variances between actual and forecasted data as shown in equation (2).

$$\text{MAPE}= \frac{1}{n}\sum_{p=1}^{n}\left|\frac{A_p - P_p}{A_p}\right| \quad (2)$$

Where A_p is the actual value and, P_p is the forecast value.

When compared to the original values, the coefficient of determination (R-squared) indicates how well the values fit together as shown in equation (3). The value is presented as a percentage and ranges from 0 to 1. The greater the value, the better the model.

$$R2 = 1 - \frac{Sum\ of\ square\ of\ Residuals}{Total\ Sum\ of\ Squares}$$

$$R^2 = 1 - \frac{\sum(f_i - \hat{f})^2}{\sum(f_i - \bar{f})^2} \quad (3)$$

Where f_i is the actual value, $\hat{f}$ is the predicted value and, $\bar{f}$ the mean value

Results and Analysis

The model is tested with test data once the parameters of the model have been defined in the training phase. Tables 5a–5e analyse and compare the RMSE, MAPE, and R2 scores of five different mutual fund NAV predictions used in our study using the univariate FLANN model, the N-BEATS model, and the NBSL model for 15, 20, 45, 63, 126, and 252 day predictions using the univariate FLANN model, the N-BEATS model, and the NBSL model. A long forecast horizon was chosen to evaluate the model’s consistency, reliability, and accuracy.

The Result of Tables of Univariate Models (5a-5e)

For all prediction horizons for the Axis Bluechip and Axis Midcap mutual funds, the N-BEATS model outperforms the FLANN model in a univariate setting. For longer prediction horizons, such as 45, 63, 126, and 252 days for both datasets, the NBSL model was unable to outperform the FLANN model. The N-BEATS model and NBSL model for the Mirae Asset Largecap Fund outperformed the FLANN model across all prediction horizons. The N-BEATS model achieved the lowest error values and highest R2 value for the Axis Bluechip, Axis Midcap, and Mirae Asset Largecap mutual funds.

For all prediction horizons for the SBI Smallcap Mutual Fund, the N-BEATS model and the NBSL model outperformed the FLANN model. Among the two proposed models, the NBSL model outperformed the N-BEATS model in terms of RMSE for 15, 20, 45, and 252 days. For all of the prediction horizons, the NBSL model outperformed the N-BEATS model in terms of MAPE values. For all prediction horizons, with the exception of 252 days, the R2 score of the NBSL model was considerably higher than the N-BEATS model. For all of the prediction horizons for the UTI Flexicap Mutual Fund, the N-BEATS model and the NBSL model outperform the FLANN model. The N-BEATS model achieved the lowest error values and highest R2 score for all of the forecast horizons among the two proposed models.

The result shows that, for all datasets and all prediction horizons, the N-BEATS model beats the FLANN model in the univariate setting. However, the NBSL model completely outperformed the FLANN model for 3 datasets, namely Mirae Asset Largecap Fund, SBI Smallcap Fund, and UTI Flexicap Fund, for all prediction horizons, while only outperforming it partially for 15 and 20 days of the prediction horizon for Axis Bluechip Fund and Axis Midcap Fund. The results also showed that as the number of forecast days increased, our proposed models—primarily N-BEATS—maintained consistency and achieved the greatest R2 value across the longest forecast period. Among the two proposed models, the N-BEATS model outperforms the NBSL model in a univariate setting across all datasets except SBI Smallcap Fund (partially).

Table 5a. Comparison of RMSE, MAPE and R2 values of different univariate models for Axis Bluechip Growth Mutual Fund

Models	Evaluation Metrics	No. of day's ahead prediction					
		15	20	45	63	126	252
Univariate FLANN	RMSE	0.4522	0.4266	0.58	0.568	0.5088	0.4989
	MAPE	0.9726	0.9203	1.2103	1.1959	1.0576	0.9598
	R^2 score	0.5175	0.7241	0.7111	0.6637	0.8201	0.9805
Univariate NBSL	RMSE	**0.3369**	**0.3197**	0.7325	0.7911	0.674	0.6557
	MAPE	**0.7529**	**0.7222**	1.4514	1.582	1.2994	1.1561
	R^2 score	**0.7322**	**0.8452**	0.5392	0.3476	0.6843	0.9663
Univariate N-BEATS	RMSE	**0.3231**	**0.3176**	**0.4866**	**0.5145**	**0.4517**	**0.432**
	MAPE	**0.6711**	**0.6693**	**0.9848**	**1.0388**	**0.8827**	**0.7707**
	R^2 score	**0.7536**	**0.8471**	**0.7967**	**0.724**	**0.8582**	**0.9854**

Table 5b. Comparison of RMSE, MAPE and R^2 values of different univariate models for Axis Midcap Growth Mutual Fund

Models	Evaluation Metrics	No. of day's ahead prediction					
		15	20	45	63	126	252
Univariate FLANN	RMSE	0.7376	0.7095	0.8606	0.8215	0.7505	0.7909
	MAPE	1.1884	1.1281	1.3169	1.2478	1.1211	1.0472
	R^2 score	0.6018	0.7322	0.7575	0.8635	0.939	0.9885
Univariate NBSL	RMSE	**0.6734**	**0.6376**	0.9331	0.9322	0.8333	1.0923
	MAPE	**1.075**	**1.0243**	1.4771	1.4464	1.1942	1.2642
	R^2 score	**0.668**	**0.7837**	0.715	0.8242	0.9248	0.9781
Univariate N-BEATS	RMSE	**0.5823**	**0.5282**	**0.6225**	**0.6129**	**0.5711**	**0.6252**
	MAPE	**0.8037**	**0.7264**	**0.9061**	**0.9127**	**0.8096**	**0.766**
	R^2 score	**0.7518**	**0.8516**	**0.8731**	**0.924**	**0.9647**	**0.9928**

Table 5c. Comparison of RMSE, MAPE and R2 values of different univariate models for Mirae Asset Largecap Growth Mutual Fund

Models	Evaluation Metrics	No. of day's ahead prediction					
		15	20	45	63	126	252
Univariate FLANN	RMSE	1.0577	1.0997	1.1366	1.1264	1.0058	1.0341
	MAPE	1.386	1.4158	1.4143	1.3854	1.1901	1.1193
	R^2 score	0.2765	0.6463	0.8262	0.8235	0.8795	0.9795
Univariate NBSL	RMSE	**0.6993**	**0.6833**	**0.8684**	**0.9069**	**0.7882**	**0.7688**
	MAPE	**0.7169**	**0.7368**	**0.9542**	**1.0089**	**0.8396**	**0.7501**
	R^2 score	**0.6838**	**0.8635**	**0.8985**	**0.8856**	**0.926**	**0.9887**
Univariate N-BEATS	RMSE	**0.679**	**0.6417**	**0.7816**	**0.8561**	**0.7619**	**0.7406**
	MAPE	**0.6027**	**0.5899**	**0.8388**	**0.9251**	**0.8035**	**0.715**
	R^2 score	**0.7019**	**0.8796**	**0.9178**	**0.898**	**0.9308**	**0.9895**

Table 5d. Comparison of RMSE, MAPE and R2 values of different univariate models for SBI Smallcap Growth Mutual Fund

Models	Evaluation Metrics	No. of day's ahead prediction					
		15	20	45	63	126	252
Univariate FLANN	RMSE	1.4999	1.3436	1.2582	1.254	1.2802	1.4147
	MAPE	1.7725	1.5062	1.3123	1.282	1.2478	1.2168
	R^2 score	0.5288	0.7244	0.8093	0.9016	0.9647	0.9875
Univariate NBSL	RMSE	**0.8783**	**0.8392**	**0.8005**	**0.8304**	**0.8329**	**0.9316**
	MAPE	**0.7994**	**0.8007**	**0.7967**	**0.8002**	**0.7096**	**0.6899**
	R^2 score	**0.8384**	**0.8925**	**0.9228**	**0.9569**	**0.9851**	**0.9946**
Univariate N-BEATS	RMSE	**0.9371**	**0.8638**	**0.8006**	**0.8284**	**0.8317**	**0.9618**
	MAPE	**0.9413**	**0.8791**	**0.8166**	**0.8153**	**0.7288**	**0.7147**
	R^2 score	**0.8161**	**0.8861**	**0.9228**	**0.9571**	**0.9851**	**0.9942**

Table 5e. Comparison of RMSE, MAPE and R2 values of different univariate models for UTI Flexicap IDCW Mutual Fund

Models	Evaluation Metrics	No. of day's ahead prediction					
		15	20	45	63	126	252
Univariate FLANN	RMSE	1.793	1.8927	2.0774	2.0512	1.8763	1.8267
	MAPE	1.0431	1.0822	1.1331	1.1122	0.9915	0.8874
	R^2 score	0.7394	0.8201	0.8333	0.8306	0.9054	0.9864
Univariate NBSL	RMSE	**1.483**	**1.4566**	**1.8377**	**1.8189**	**1.6408**	**1.6976**
	MAPE	**0.9173**	**0.8884**	**1.0536**	**1.0321**	**0.8606**	**0.7816**
	R^2 score	**0.8217**	**0.8934**	**0.8696**	**0.8668**	**0.9277**	**0.9883**
Univariate N-BEATS	RMSE	**1.3384**	**1.2918**	**1.5896**	**1.5857**	**1.4783**	**1.4734**
	MAPE	**0.7754**	**0.7316**	**0.9008**	**0.8982**	**0.7862**	**0.6854**
	R^2 score	**0.8548**	**0.9162**	**0.9024**	**0.8987**	**0.9413**	**0.9912**

Figures 7a, 7b, 7c, 7d, and 7e show univariate NAV forecast graphs for five different NAV datasets over 252 forecasting days. The graphs for the largest prediction period of 252 days in univariate settings were chosen to be displayed in comparison to the other forecast periods because they had the best accuracy, particularly for the N-BEATS model, which has outperformed nearly all other models in every prediction horizon. The green line in each graph depicts the actual NAV values, while the purple line shows the FLANN model's NAV prediction trend, the yellow line shows the NBSL model's prediction trend, and the black line displays the N-BEATS model's NAV forecast trend.

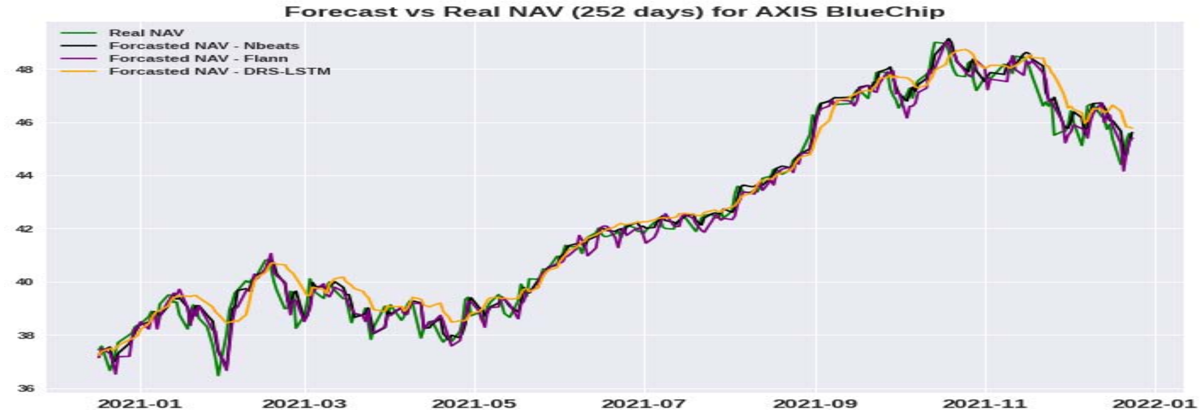

Figure 7a. Comparison of forecast values by univariate models for Axis Bluechip Growth Fund over a period of 252 days

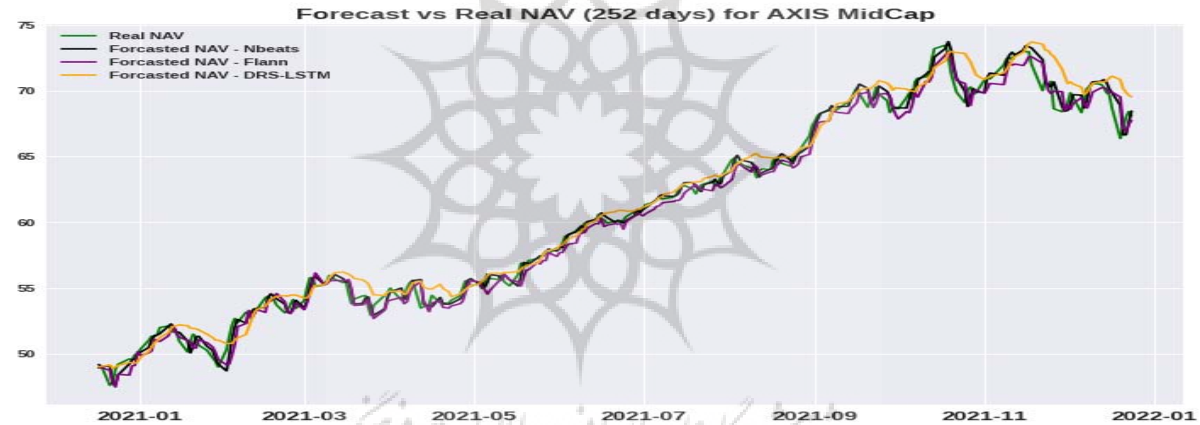

Figure 7b. Comparison of forecast values by univariate models for Axis Midcap Growth Fund over a period of 252 days

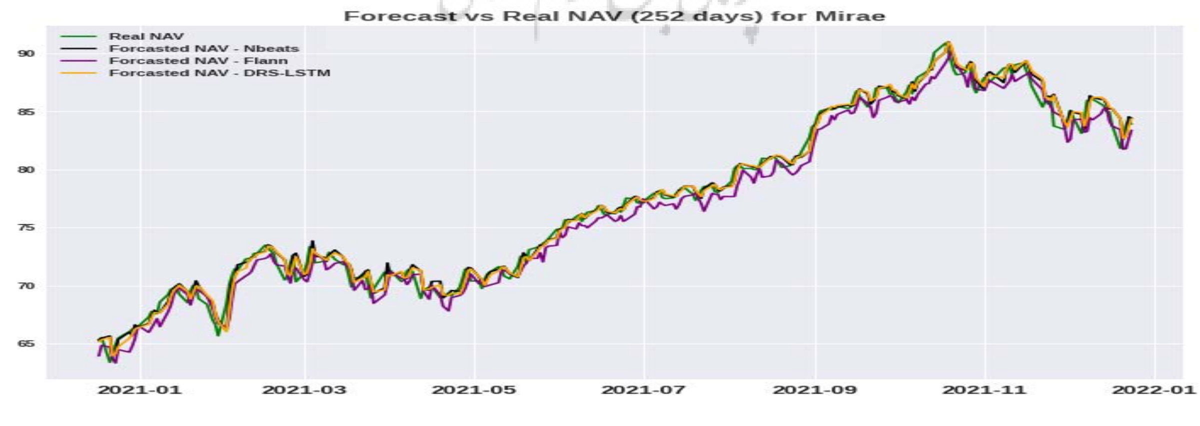

Figure 7c. Comparison of forecast values by univariate models for Mirae Asset Largecap Growth Fund over a period of 252 days

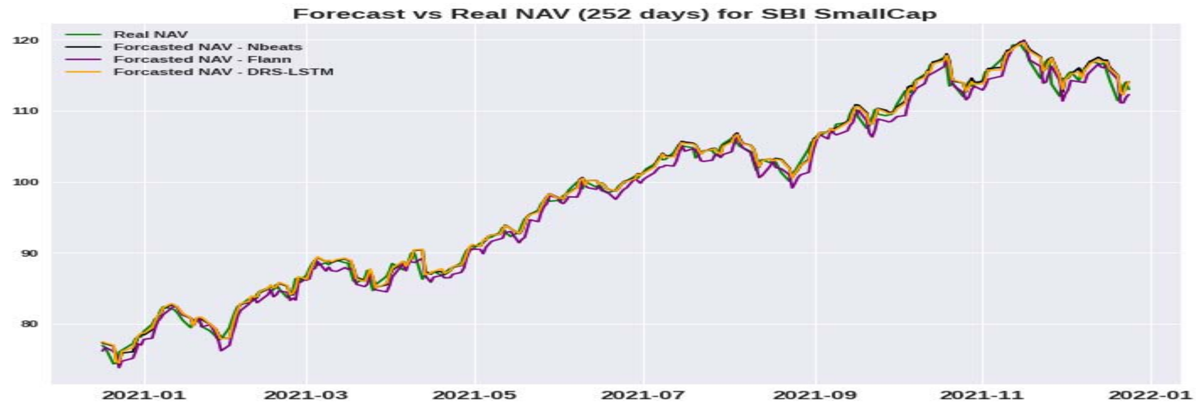

Figure 7d. Comparison of forecast values by univariate models for SBI Smallcap Growth Fund over a period of 252 days

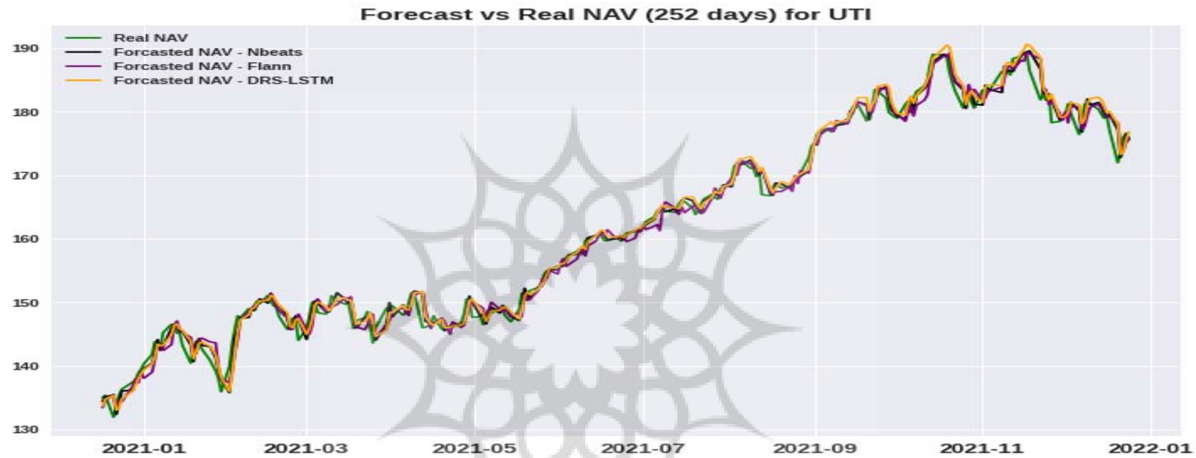

Figure 7e. Comparison of forecast values by univariate models for UTI Flexicap IDCW Fund over a period of 252 days

The Result of Tables of Multivariate Models (6a-6e)

Tables 6a–6e analyse and compare the RMSE, MAPE, and R2 scores of five different mutual fund NAV predictions used in our study using the multivariate FLANN model, the N-BEATS model, and the NBSL model for 15, 20, 45, 63, 126, and 252 day predictions using the multivariate FLANN model, the N-BEATS model, and the NBSL model.For the Axis Bluechip and Axis Midcap mutual funds, the N-BEATS model performed better than the FLANN model throughout all the prediction horizons. The NBSL model, however, was unable to beat the FLANN model on any prediction horizon for both datasets.

The N-BEATS model and NBSL model for the Mirae Asset Largecap Fund outperformed the FLANN model across all prediction horizons. Among the two proposed models, the NBSL model outperformed the N-BEATS model in terms of RMSE and R2 score for 15 and 20 days of the prediction horizon, respectively. The N-BEATS model outperformed the NBSL model for the remaining prediction horizons. For the SBI Smallcap and UTI Flexicap Mutual Funds, the N-BEATS model and NBSL model outperformed the

FLANN model across all prediction horizons. In comparison to the NBSL model, the N-BEATS model performed much better.

The result in a multivariate setting shows that for all datasets and all prediction horizons, N-BEATS models outperform the FLANN model. However, the NBSL model excelled for three datasets, including Mirae Asset Largecap Fund, SBI Smallcap Fund, and UTI Flexicap Fund, while underperforming for two datasets, Axis Bluechip Fund and Axis Midcap Fund. The results also showed that as the number of forecast days increased, our proposed models—primarily N-BEATS—maintained consistency and achieved the greatest R2 value across the longest forecast period. Among the two proposed models, the N-BEATS model outperforms the NBSL model in a multivariate setting across all datasets except Mirae Asset Largecap Fund (partially).

Table 6a. Comparison of RMSE, MAPE and R2 values of different multivariate models for Axis Bluechip Growth Mutual Fund

Models	Evaluation Metrics	No. of day's ahead prediction					
		15	20	45	63	126	252
Multivariate FLANN	RMSE	0.4186	0.3928	0.5618	0.5634	0.498	0.4859
	MAPE	0.8529	0.8192	1.1659	1.1662	1.0051	0.9122
	R^2 score	0.5864	0.7661	0.7289	0.6691	0.8276	0.9815
Multivariate NBSL	RMSE	0.4576	0.4317	0.7676	0.7969	0.6631	0.7699
	MAPE	1.1097	1.0084	1.5947	1.653	1.3213	1.3307
	R^2 score	0.5057	0.7176	0.494	0.338	0.6944	0.9535
Multivariate N-BEATS	RMSE	0.3477	0.3486	0.5429	0.5462	0.4744	0.4273
	MAPE	0.7172	0.7238	1.0501	1.0664	0.9104	0.7602
	R^2 score	0.7146	0.8159	0.7469	0.6891	0.8436	0.9857

Table 6b. Comparison of RMSE, MAPE and R2 values of different multivariate models for Axis Midcap Growth Mutual Fund

Models	Evaluation Metrics	No. of day's ahead prediction					
		15	20	45	63	126	252
Multivariate FLANN	RMSE	0.7683	0.7331	0.8683	0.8254	0.7597	0.8014
	MAPE	1.2359	1.1602	1.3225	1.2512	1.1375	1.0693
	R^2 score	0.5679	0.7141	0.7532	0.8622	0.9375	0.9882
Multivariate NBSL	RMSE	0.8397	0.7922	1.0047	0.9674	0.8352	1.1818
	MAPE	1.5504	1.4095	1.684	1.5652	1.2893	1.3707
	R^2 score	0.4838	0.6662	0.6695	0.8107	0.9244	0.9743
Multivariate N-BEATS	RMSE	0.5404	0.4958	0.5435	0.5611	0.5396	0.5904
	MAPE	0.7331	0.6897	0.8193	0.8419	0.756	0.7089
	R^2 score	0.7862	0.8692	0.9033	0.9363	0.9685	0.9936

Table 6c. Comparison of RMSE, MAPE and R2 values of different multivariate models for Mirae Asset Largecap Growth Mutual Fund

Models	Evaluation Metrics	No. of day's ahead prediction					
		15	20	45	63	126	252
Multivariate FLANN	RMSE	1.1183	1.1801	1.1919	1.1699	1.0615	1.1051
	MAPE	1.5027	1.5578	1.4982	1.4381	1.2677	1.2092
	R^2 score	0.1913	0.5927	0.8088	0.8096	0.8657	0.9766
Multivariate NBSL	RMSE	0.7195	0.7111	0.905	0.9376	0.8088	0.7812
	MAPE	0.7799	0.8023	0.9909	1.0379	0.8613	0.7697
	R^2 score	0.6652	0.8521	0.8898	0.8777	0.9221	0.9883
Multivariate N-BEATS	RMSE	0.7426	0.7123	0.8598	0.8929	0.787	0.7434
	MAPE	0.7366	0.7321	0.938	0.9839	0.8266	0.7321
	R^2 score	0.6434	0.8516	0.9005	0.8891	0.9262	0.9894

Table 6d. Comparison of RMSE, MAPE and R2 values of different multivariate models for SBI Smallcap Growth Mutual Fund

Models	Evaluation Metrics	No. of day's ahead prediction					
		15	20	45	63	126	252
Multivariate FLANN	RMSE	1.4455	1.3005	1.2083	1.2039	1.2224	1.348
	MAPE	1.7064	1.4674	1.2669	1.2359	1.1884	1.1524
	R2 score	0.5624	0.7418	0.8241	0.9093	0.9678	0.9887
Multivariate NBSL	RMSE	**1.0072**	**0.9222**	**0.8721**	**0.8952**	**0.8865**	**1.08**
	MAPE	**1.0376**	**0.9539**	**0.9017**	**0.8933**	**0.7816**	**0.7797**
	R2 score	**0.7875**	**0.8702**	**0.9084**	**0.9499**	**0.9831**	**0.9927**
Multivariate N-BEATS	RMSE	**0.8219**	**0.7766**	**0.7193**	**0.758**	**0.7973**	**0.9014**
	MAPE	**0.7797**	**0.7576**	**0.7159**	**0.7358**	**0.695**	**0.6781**
	R2 score	**0.8585**	**0.9079**	**0.9377**	**0.9641**	**0.9863**	**0.9949**

Table 6e. Comparison of RMSE, MAPE and R2 values of different multivariate models for UTI Flexicap IDCW Mutual Fund

Models	Evaluation Metrics	No. of day's ahead prediction					
		15	20	45	63	126	252
Multivariate FLANN	RMSE	1.74	1.8392	2.062	2.0401	1.8655	1.8164
	MAPE	1.0031	1.0482	1.1228	1.1026	0.9778	0.8765
	R2 score	0.7546	0.8301	0.8358	0.8324	0.9065	0.9866
Multivariate NBSL	RMSE	**1.3818**	**1.3637**	**1.9628**	**1.9392**	**1.7499**	**1.7346**
	MAPE	**0.7474**	**0.7587**	**1.0713**	**1.0663**	**0.8952**	**0.7977**
	R2 score	**0.8452**	**0.9066**	**0.8512**	**0.8486**	**0.9177**	**0.9877**
Multivariate N-BEATS	RMSE	**1.3557**	**1.3112**	**1.4624**	**1.5027**	**1.4547**	**1.465**
	MAPE	**0.7062**	**0.7017**	**0.8155**	**0.8429**	**0.764**	**0.6743**
	R2 score	**0.851**	**0.9137**	**0.9174**	**0.9091**	**0.9431**	**0.9913**

Figures 8a, 8b, 8c, 8d, and 8e show multivariate NAV forecast graphs for five different NAV datasets over 252 forecasting days. When compared to the other forecast periods, the graphs for the largest prediction period of 252 days for multivariate settings were chosen to be shown because they were the most accurate, especially for the N-BEATS model, which has done better than almost every other model in every prediction horizon.The green line in each graph depicts the actual NAV values, while the purple line shows the FLANN model's NAV prediction trend, the yellow line shows the NBSL model's prediction trend, and the black line displays the N-BEATS model's NAV forecast trend.

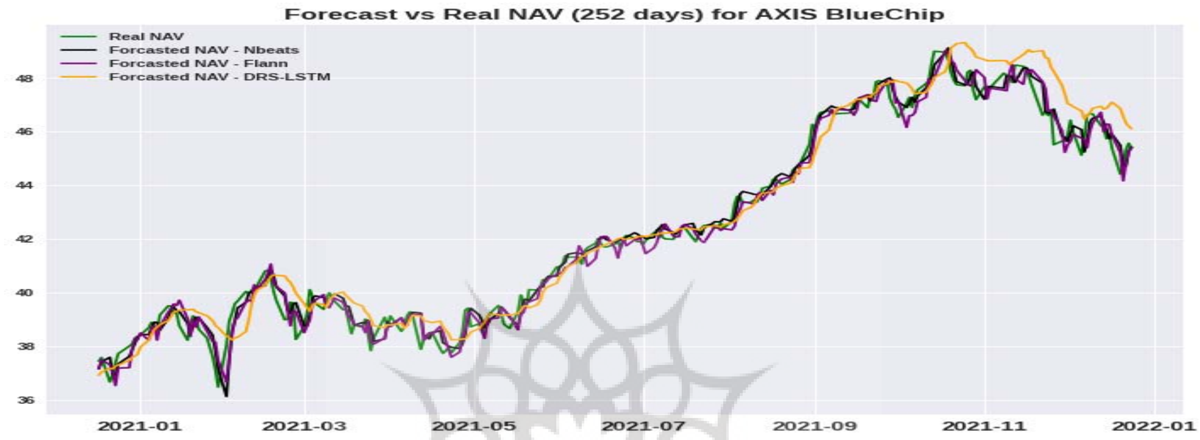

Figure 8a. Comparison of forecast values by multivariate models for Axis Bluechip Fund over a period of 252 days

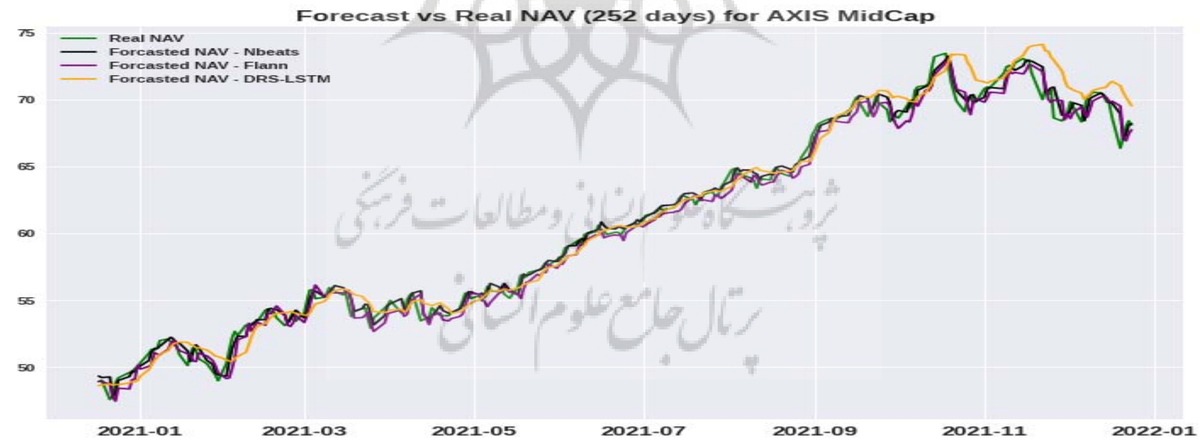

Figure 8b. Comparison of forecast values by multivariate models for Axis Midcap Fund over a period of 252 days

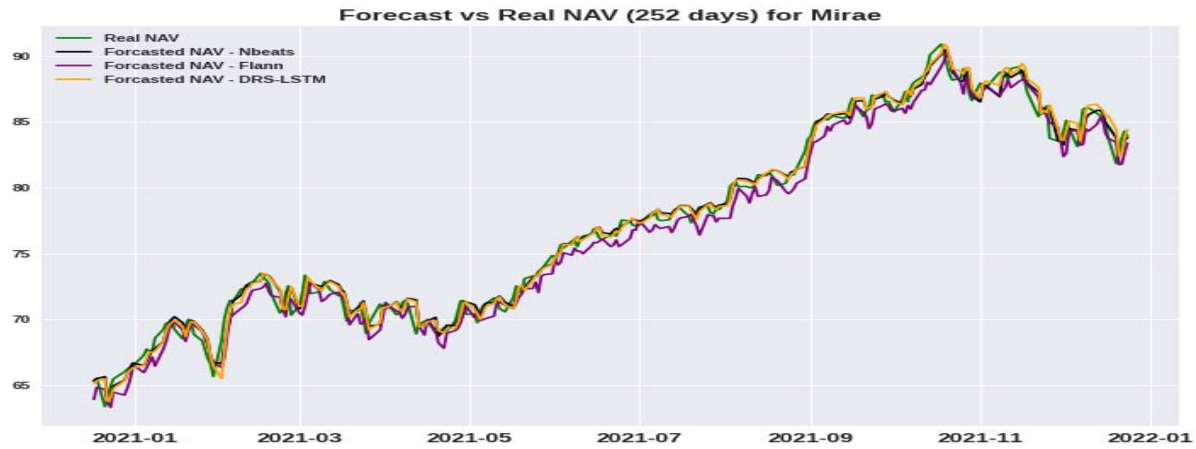

Figure 8c. Comparison of forecast values by multivariate models for Mirae Asset Largecap Fund over a period of 252 days

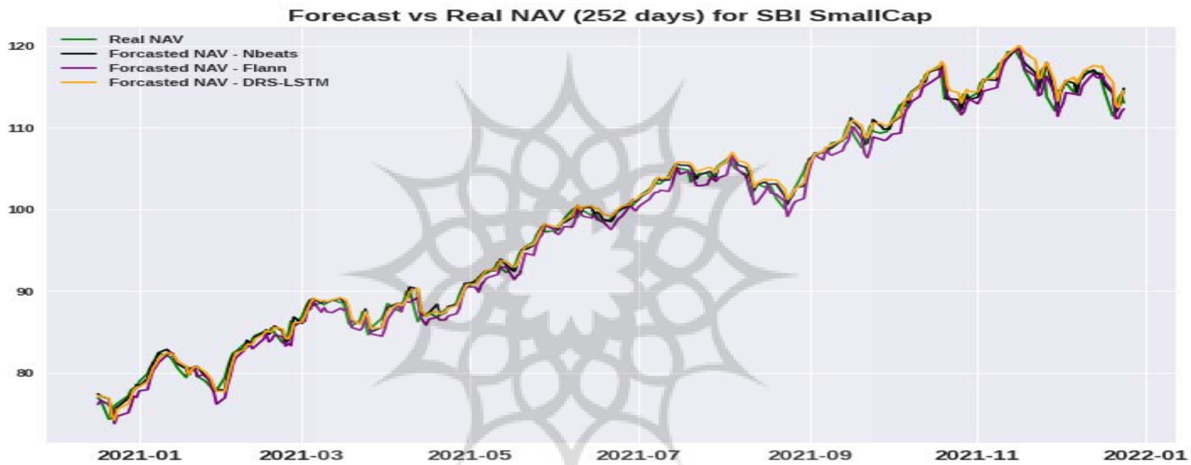

Figure 8d. Comparison of forecast values by multivariate models for SBI Smallcap Fund over a period of 252 days

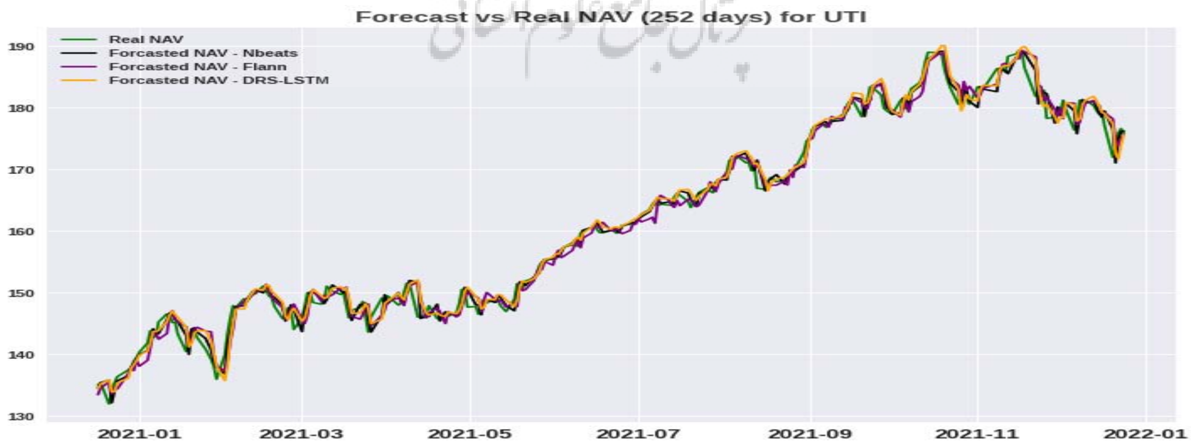

Figure 8e. Comparison of forecast values by multivariate models for UTI Flexicap Fund over a period of 252 days

Conclusion

Our research focuses on the experimental comparison of the Net Asset Value (NAV) prediction performance of our proposed deep learning models, such as N-BEATS and NBSL, with the FLANN model in both univariate and multivariate settings of five eminent Indian mutual funds, namely Axis Bluechip Growth Fund, Axis Midcap Growth Fund, Mirae Asset Large Cap Growth Fund, SBI Small Cap Growth Fund, and UTI Flexi Cap IDCW Fund, for forecast periods of 15, 20, 45, 63, 126, and 252 days. For the multivariate analysis, we have used the MCX, BSE SENSEX as independent variables. The models' performance is evaluated using the following three assessment metrics: RMSE, MAPE, and R2. The result reveals that the N-BEATS model outperforms the FLANN model in the univariate setting for all datasets and all prediction horizons. For three datasets, namely Mirae Asset Largecap Fund, SBI Smallcap Fund, and UTI Flexicap Fund, the NBSL model completely outperformed the FLANN model for all prediction horizons, while only partially outperforming it for 15 and 20 days of the prediction horizon for Axis Bluechip Fund and Axis Midcap Fund. The result also shows that our suggested models, notably N-BEATS, maintained consistency and attained the highest R2 value across the longest forecast period as the number of forecast days rose. In a univariate setting, among the two proposed models, the N-BEATS model performs better than the NBSL model across all datasets except the SBI Smallcap Fund (partially).

In a multivariate setting, the result shows that N-BEATS models outperform the FLANN model across all datasets and prediction horizons. The Axis Bluechip Fund and Axis Midcap Fund were the two datasets where the NBSL model underperformed, whereas the Mirae Asset Largecap Fund, SBI Smallcap Fund, and UTI Flexicap Fund were the three datasets where it excelled. The result also shows that, as the number of forecast days grew, our suggested models, notably N-BEATS, maintained consistency and attained the highest R2 value throughout the longest forecast duration. In a multivariate setting, among the two proposed models, the N-BEATS model performs better than the NBSL model across all datasets except Mirae Asset Largecap Fund (partially). As NAV is considered one of the most important performance measures of mutual funds, our study can assist investors and financial advisors in investing in equity-based mutual funds across a range of forecasting horizons. Our suggested model may be used to anticipate a wide range of financial time-series data. Furthermore, our suggested model may be integrated with other top-performing models to construct an ensemble model for improved prediction performance in the future.

Conflict of interest

The authors of this paper state that they do not have any competing financial interests or personal relationships that could have influenced their work. We would like to verify that there are no conflicts of interest related to this publication and that no significant financial support has been received that could have influenced the outcome of the research. This statement indicates that the authors have taken steps to ensure that their work is unbiased and free from any undue influence.

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