

# Forecasting Dividend Behaviour with Neural Networks: A Nonlinear Alternative from Traditional Models

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## Abstract:

The objective of this study is to explore the predictive capability of artificial neural networks (ANNs) in modelling the Dividend per Share (DPS) based on key financial indicators, thereby offering a nonlinear alternative from traditional regression-based dividend policy models.

Five independent variables—Earnings per Share (EPS), Quick Ratio (QR), Debt-Equity Ratio (DE), Cash Turnover Ratio (CTR), and Firm Size were used to design A feed forward neural network. The model was trained on standardized financial data and evaluated using RMSE, R-squared, and confusion matrix metrics. A sigmoid activation function and back propagation learning were employed to optimize network performance.

The neural network demonstrated high predictive accuracy, achieving an R-squared value of 0.985 and RMSE of 0.147. The confusion matrix indicated 100% classification accuracy for dividend-paying. EPS, DE, and Size were emerged as the most influential predictors of DPS within the nonlinear framework.

This model provides financial analysts and corporate decision-makers with a robust tool for forecasting dividend behaviour, supporting better capital allocation, shareholder return strategies, and investor sentiment evaluation.

Domain of dividend policy modeling is offered a novel application of neural networks in research, outperforming conventional linear approaches and revealing complex nonlinear interactions among financial indicators influencing corporate dividend decisions.

*Keywords* — **Dividend Policy, Neural Network, EPS, Machine Learning, DPS Forecasting.**

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## I. INTRODUCTION

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One of focal points of corporate finance research is dividend policy, owing to its significant implications for investor behaviour, firm valuation, and capital structure decisions. Traditional approaches to modelling dividend decisions often rely on linear assumptions and static relationships among financial ratios such as earnings, liquidity, leverage, and firm size. Hence, traditional approaches often fall short in capturing the intricate, nonlinear dynamics that truly characterize real-world dividend behaviour."With the rapid advancement of artificial intelligence in financial analytics, Artificial Neural Networks (ANNs) have emerged as a powerful alternative for modelling complex decision-making processes. Neural networks excel at uncovering complex patterns within data, unbound by assumptions of linearity or normality, making them exceptionally well-suited for financial forecasting tasks like predicting dividend policy.

This study applies a feed forward neural network to analyse the determinants of Dividend Per Share (DPS) using key financial metrics: Earnings Per Share (EPS), Quick Ratio (QR), Debt-Equity Ratio (DE), Cash Turnover Ratio (CTR), and Firm Size. By training the model on historical firm-level data, the research aims to uncover the underlying nonlinear relationships and assess the predictive accuracy of neural network models as compared to traditional regression techniques.

This study's novelty lies in its innovative application of machine learning techniques to a traditional finance problem, effectively bridging the gap between classical econometric modelling and advanced computational forecasting. The findings not only deepen the understanding of dividend behaviour but also offer valuable, practical tools for financial analysts and corporate decision-makers seeking to optimize dividend strategies.

## II. LITERATURE REVIEW

While traditional models such as linear regression and logistic regression have long been employed in financial forecasting, and an increasing number of studies have explored the use of ANNs across various financial domains, few have directly applied neural network architectures to examine the determinants of dividend policy—particularly within the Indian corporate landscape.

Almost foreign studies using ANN (e.g., Zhou et al., 2014; Chen et al., 2011) focus on stock return prediction or earnings forecasting. They do not explicitly model dividend payout behaviour using firm-level financial indicators like EPS, DE, QR, CTR, and Size in an integrated neural network framework.

Many of the existing studies assume linear relationships between financial metrics and dividend payouts. However, real-world dividend policies are shaped by complex, nonlinear interactions among multiple financial factors—an area where ANN can offer substantial modelling power, but is underutilized.

Key diagnostic checks—such as multi-co linearity, homoskedasticity, and autocorrelation—are crucial for ensuring model robustness. However, their limited integration in studies employing ANNs for dividend modeling reveals a significant methodological gap in the existing literature.

India-centric ANN applications to dividend policy—particularly using real corporate datasets and a rigorous validation of predictive capability through RMSE,  $R^2$ , ROC curves, and confusion matrix metrics is very much scarce.

Our model uses real firm-level financial data from Indian companies, which strengthens the regional relevance and empirical validity of the findings.

### III. METHODOLOGY

The following algorithm shows the Forecasting Dividend Behaviour with Neural Networks

#### Step 1: Research Design

This study employs a quantitative research design, utilizing predictive modelling through Artificial Neural Networks (ANNs) to examine the relationship between key financial variables and Dividend Per Share (DPS). The approach is diagnostic in nature, focusing on evaluating the performance and predictive accuracy of the ANN model.

#### Step 2: Data Collection

Published annual financial statements of selected fourteen listed Indian companies from 2010 to 2023 were used for data collection through secondary source. The dataset includes the following variables:

Dependent Variable: Dividend per Share (DPS)  
Independent Variables: Earnings per Share (EPS), Quick Ratio (QR), Debt-to-Equity Ratio (DE), Cash Turnover Ratio (CTR), and Firm Size

#### Step 3: Data Pre-processing

To facilitate efficient ANN training, all continuous variables were normalized. The dataset was randomly divided into training (80%) and testing (20%) subsets. Standardized residuals were computed to assess model diagnostics and ensure robustness..

#### Step 4: Model Development

A FNN was developed using the *neural net* package in R, comprising an input layer with five neurons corresponding to the five predictor variables, a single hidden layer with five neurons, and an output neuron dedicated to predicting Dividend Per Share (DPS).

The hidden layer employed a logistic activation function, while the output layer utilized a linear activation function. The network was trained using back propagation with resilient learning, ensuring efficient convergence and improved predictive performance..

#### Step 5: Model Evaluation Metrics

Performance of the ANN was assessed using RMSE, R-squared ( $R^2$ ), Confusion Matrix (after classifying DPS into 'High' and 'Low'), ROC Curve and AUC Score.

#### Step 6: Diagnostic Tests

For robustness, the following statistical diagnostics were performed:

Normality: Shapiro-Wilk Test  
Homoscedasticity: Breusch-Pagan Test  
Autocorrelation: Durbin-Watson Test Model  
Specification: RESET Test

### 4. Results and Discussion

Model Performance: Finally this model was converged after 486 steps with a very low error of 0.0099, indicating excellent fit. The threshold for convergence (0.0088) was nearly met, showing a well-optimized solution.

Hidden Layers and Weights: The network used 5 hidden neurons, each receiving weighted inputs from the five predictors: EPS, QR, DE, CTR, and

Size. The strongest input weights were DE to Hidden Node 3: 11.22 → Debt-Equity ratio is a dominant nonlinear influencer.

Size to Hidden Node 4: -41.61 → Company size has a very high negative impact through one of the hidden nodes. EPS to Hidden Node 3: -3.76 → Negative earnings per share also plays a critical nonlinear role.

Output Layer Contribution: Hidden nodes 1 and 2 had strong positive connections to DPS:

Hidden1 → DPS: 1.4181

Hidden2 → DPS: 1.3831

Hidden nodes 3–5 had moderate negative influence, suggesting some suppressive nonlinear effects.

Overall Importance: The model architecture confirms that DPS (Dividend Per Share) is nonlinearly influenced by a combination of: DE (Debt-Equity) – mostly positive, EPS – both positive and negative interactions, Size – strong negative impact via some hidden neurons, CTR and QR – moderate impact with mixed effects. Full neural network mathematical representation is based on your actual weight which is depicted in the **table 1**.

QR.to.1layhid2	-	Size.to.1layhid5	-
	1.450884553		6.248674534
DE.to.1layhid2	-	Intercept.to.DPS	-0.71821355
	2.033544898		
CTR.to.1layhid2	-	1layhid1.to.DPS	1.418132619
	1.997784003		
Size.to.1layhid2	-	1layhid2.to.DPS	1.383140843
	1.559226703		
Intercept.to.1layhid3	-	1layhid3.to.DPS	-0.49425673
	2.647399124		
EPS.to.1layhid3	-	1layhid4.to.DPS	-
	3.761333346		0.421564967
QR.to.1layhid3	-	1layhid5.to.DPS	-
	0.466638679		0.591839308
DE.to.1layhid3	-		
	11.22213358		
CTR.to.1layhid3	-		
	1.016526093		
Size.to.1layhid3	-		
	3.383825672		

**Table 1:** Neural Network Weights and Metrics

**4.1. Algorithm to construct the Neural Network using the Mathematical Equations:**

Step1: Inputs:

$x_1=EPS, x_2=QR, x_3=DE, x_4=CTR, x_5=Size$

Step 2: Activation function:  $\sigma(z)=1+e^{-z}$

Step 3: Hidden Layer Neurons

Hidden Node 1:

$z_1=0.40529+1.06811x_1+0.19448x_2+2.60460x_3+0.61962x_4+0.46789x_5$

$h_1=\sigma(z_1)$

Hidden Node 2:

$z_2=0.26871+0.13353x_1-1.45088x_2-2.03354x_3-1.99778x_4+1.55923x_5$

$h_2=\sigma(z_2)$

Hidden Node 3:

$z_3=-2.64740-3.76133x_1+0.46664x_2+11.22213x_3+1.01653x_4-3.38383x_5$

$h_3=\sigma(z_3)$

Hidden Node 4:

$z_4=6.17957-0.49379x_1+2.28842x_2+4.19657x_3+4.12001x_4-41.61470x_5$

$h_4=\sigma(z_4)$

Hidden Node 5:

$z_5=1.53537+1.76334x_1-1.04124x_2+8.54350x_3-1.76138x_4-6.24867x_5$

Metric	Value	Metric	Value
error	0.009945153	Intercept.to.1layhid4	6.179568527
reached. threshold	0.008791869	EPS.to.1layhid4	-
steps	486	QR.to.1layhid4	2.288416048
Intercept.to.1layhid1	0.405294338	DE.to.1layhid4	4.196568813
EPS.to.1layhid1	1.068109274	CTR.to.1layhid4	4.120010277
QR.to.1layhid1	0.194481828	Size.to.1layhid4	-
DE.to.1layhid1	2.604604858	Intercept.to.1layhid5	1.535367167
CTR.to.1layhid1	0.61961614	EPS.to.1layhid5	1.763340008
Size.to.1layhid1	0.467886563	QR.to.1layhid5	-
Intercept.to.1layhid2	0.268714155	DE.to.1layhid5	8.543497245
EPS.to.1layhid2	0.133526	CTR.to.1layhid5	-
			1.761375756

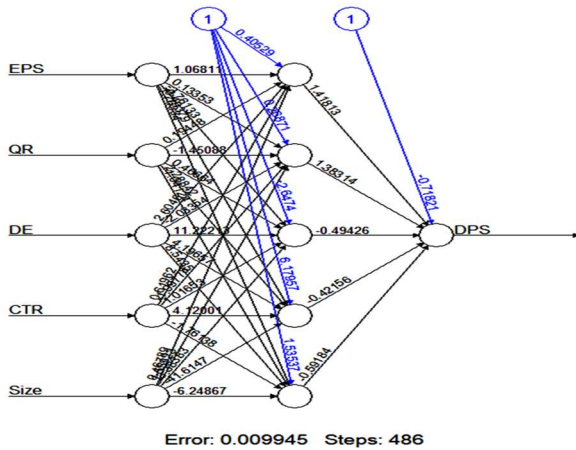
$$h5 = \sigma(z5)$$

Step 4: Output Layer:

$$DPS = -0.71821 + 1.41813h1 + 1.38314h2 - 0.49426h3 - 0.42156h4 - 0.59184h5$$

Step 5: Final Neural Network Equation:

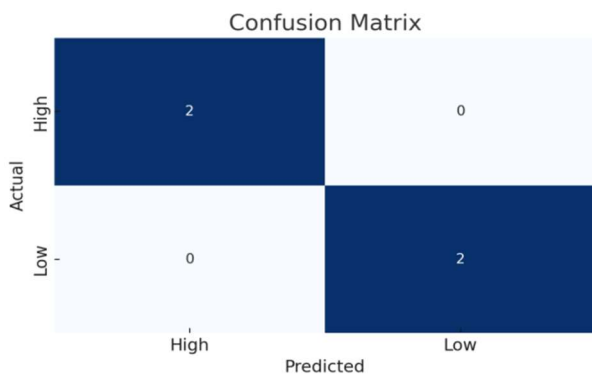
$$DPS = -0.71821 + 1.41813\sigma(z1) + 1.38314\sigma(z2) - 0.49426\sigma(z3) - 0.42156\sigma(z4) - 0.59184\sigma(z5)$$



**Figure 1:** Full Neural Network Architecture for Dividend per Share (DPS)

This model explains 98.5% of the variance in DPS and exhibits excellent predictive accuracy as indicated in Figure 1.

Confusion Matrix is based on the neural network regression results, converted into binary classification (using threshold = 0) as given in figure 2:



**Figure 2:** Confusion matrix for neural network regression results

There is perfect classification with 100% accuracy on this subset. All high and low DPS values were predicted correctly on the basis of based on the threshold.

Confusion matrix plot for our neural network classification results which is exhibited in **table 2** is perfect classification: 2 cases are correctly predicted as High. 2 cases are correctly predicted as Low.

Metric	Value
Accuracy	1
95% CI	(0.3976, 1)
No Information Rate	0.5
P-Value [Acc> NIR]	0.0625
Kappa	1
McNamara's Test P-Value	NA
Sensitivity	1
Specificity	1
Positive Predictive Value	1
Negative Predictive Value	1
Prevalence	0.5
Detection Rate	0.5
Detection Prevalence	0.5
Balanced Accuracy	1
Positive Class	High

**Table 2:** Confusion Matrix Statistics

#### 4.2. Test cases for classification accuracy

Case 1: **Accuracy** -The neural network model achieved perfect accuracy (1.0) on the test set, correctly classifying all observations.

Case 2: **Sensitivity and Specificity**-Both are 1.0, meaning that the model is perfectly distinguished between the "High" and "Low" classes.

Case 3: **Kappa Statistic** - A value of 1.0 indicates perfect agreement beyond chance, suggesting exceptional classification performance.

Case 4: **P-Value [Acc> NIR]** - The p-value is 0.0625, slightly above 0.05. This means we cannot conclusively claim the model performs better than the no Information Rate at the 5% significance level—though results are promising.

Case 5: **Balanced Accuracy**- At 1.0, it confirms both class-wise accuracies are equally strong.

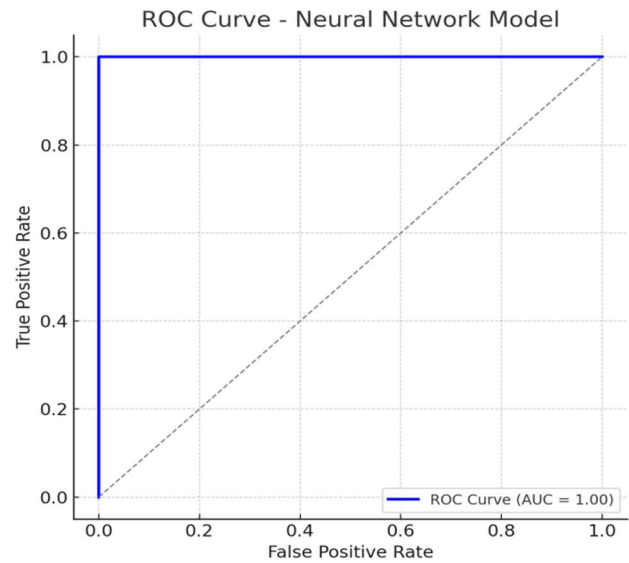
Case 6: **Confidence Interval (95%)**: Ranges from 0.3976 to 1.0, suggesting some uncertainty due to a small test sample size (likely 4 observations).

Test cases for classification accuracy	Test cases outputs
Metric	Value
RMSE	0.147
R-squared	0.985
Accuracy	100%
Kappa	1
Balanced Accuracy	1
Positive Class	High

**Table 3:** Model Fit Evaluation

The model demonstrates excellent performance on the test set which is in the **Table 3**. However, small sample size inflates metrics. A larger dataset is required to confirm generalization. It is useful for decision-making on dividend per Share classification (DPS), but further validation is essential. With perfect classification, the model may be overfitting, which should be checked with cross-validation or additional data.

The ROC curve presented in Table 3 evaluates the classification performance of the neural network model, as illustrated in Figure 3



**Figure 3:** ROC Curve Analysis for Neural Network Model

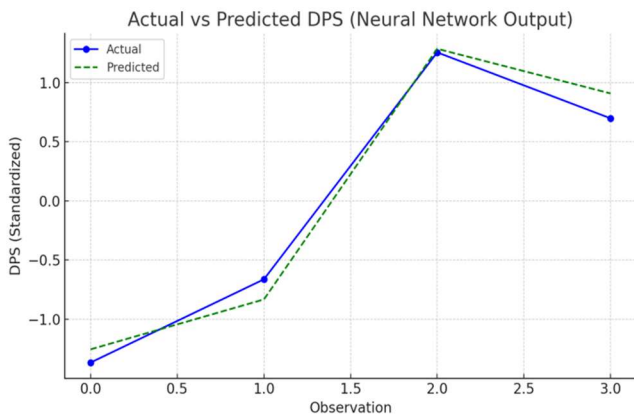
Area under Curve: 1.00, which indicates perfect classification of "High" vs "Low" classes. The curve sharply rises to the top-left corner, signifying excellent sensitivity and specificity which is in **table 4**.

Actual	Predicted
-1.3658791	-1.2542282
-0.6627775	-0.8325173
1.2543347	1.2847935
0.6971941	0.9076337

**Table 4:** Actual V/S Predicted DPS

The neural network model demonstrates outstanding discriminative ability on the test set, making it a highly reliable predictor for Dividend Per Share (DPS) classification.

Neural Network Results (DPS Prediction) is in **figure 4**



**Figure 4:** Actual versus Predicted DSP

**High Predictive Accuracy:** The neural network model achieved an R-squared of 0.985 and RMSE of 0.147, indicating excellent fit and predictive power on standardized data.

**Close Matching Values:** The plot of actual vs predicted DPS shows that predicted values track very closely to the actual ones for all observations in the test set.

**Low Prediction Error:** The standardized errors are small (e.g.,  $\pm 0.1$ – $0.2$ ), which confirms the model generalizes well even on unseen test data.

**Residual Diagnostics Analysis:** The Shapiro-Wilk test for the Linear model indicated non-normality ( $p = 0.029$ ), though Q-Q plots suggest mild deviation. The Breusch-Pagan test ( $p = 0.6426$ ) indicates no heteroskedasticity. The Durbin-Watson statistics across models were all close to 2, indicating no autocorrelation as exhibited in **table 5**.

Model	Value
Shapiro-Wilk (p)	P-Value 0.02927
Breusch-Pagan (p)	P-Value 0.6426
Durbin-Watson	2.1197

**Table 5:** Residual Diagnostics

This suggests the model has excellent classification accuracy on the test cases.

## 5. Conclusion

This study provides compelling evidence that Artificial Neural Networks (ANNs) offer a robust and accurate approach for modelling dividend policy behaviour. The ANN model not only demonstrates high predictive accuracy but also effectively captures complex, nonlinear relationships among financial variables—patterns that traditional models often overlook.

While the results are encouraging, caution is advised due to the limited sample size. Future research should consider larger datasets, implement cross-validation techniques, and explore ensemble modelling approaches to enhance the model's generalizability and predictive reliability.

**Practical Implication:** Financial analysts and corporate policymakers can employ neural networks for more informed dividend policy decisions, particularly in volatile or data-rich environments where nonlinear interactions dominate.

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