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USING NEURAL NETWORKS IN STRATEGIC MARKETING DECISION MAKING

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ABSTRACT:

The usage of Artificial Intelligence (AI) in marketing is a topic of special interest in the industry today. The applications of AI are immense, ranging from automation and predictive analytics, to modelling consumer behaviour. With the emergence of Big Data, Neural Networks have become an incredibly useful tool for marketing decision making.

In this study, we have examined the application of Neural Networks in taking strategic marketing decisions employing an exploratory research methodology. We have used the output results from a simulation software, Pharmasim. First, the teams were segmented using a cluster analysis approach and high performers, moderate performers and poor performers were identified among all the teams. A 3-cluster approach was identified to be the most appropriate to segment the teams, and a MANOVA was carried out to test whether the differences in performance was statistically significant.

A neural network was developed on MATLAB to test whether a Machine Learning (ML) algorithm could replicate the same decisions that human intelligence would take, given the same information and conditions. The ML algorithm was run for two parameters- to predict the 10-year average stock price for each team, considering the average performance parameters over the same 10-year period. The second algorithm was developed for the dashboard parameters to test the application of ML algorithms in measuring the marketing dashboard effectiveness. We concluded the study with a discussion of the findings and decision-making implications.

INTRODUCTION

The application of Artificial intelligence (AI) techniques to marketing is a relatively new concept. The convergence of AI and marketing is specifically applicable to market forecasting and aids in decision making. Organizations are currently implementing AI to their marketing techniques and the initial results are promising. Business and technology executives opine that AI can significantly help organizations improve their customer satisfaction and help the organizations achieve improve the product line. According to Forbes organizations implementing AI in their organizational framework have reported up to 75% increase in customer satisfaction levels.

A neural network is composed of interconnected nodes, known as neurons or nodes.

The computing system is inspired by the human brain, and the learning characteristics are based on the learning materials that is input into the network. Neural networks were primarily developed to solve problems like a human brain would; the choice of a model is also dependent on the following parameters:

- **Choice of Model:** Like statistical models, complex models slow down the learning process. Simpler models are easier to train, but might not be as effective as a more complex model in understanding and explaining the interplay between various factors
- **Learning algorithm:** The learning algorithm also significantly influences the training process. Complicated algorithms slow down the training process; however, using simplistic models also might not be able to fully understand and explain the dataset
- **Robustness:** Robust models are more complex to build and understand, but they can provide a detailed understanding of the results.

OBJECTIVES:

This study was conducted to determine three pertinent questions driving current research pertaining to the impact of neural networks in Marketing.

1.) Are Neural Networks able to replicate human decision making, given the same inputs that the teams had access to, during the simulation?

2.) Can Neural Networks predict performance parameters successfully?

3.) How effective is a Neural Network in evaluating the marketing performance, as reflected in a marketing dashboard?

To address these research questions, we developed a neural network using MATLAB. As a response to the first two questions, we used the average performance parameters to model the network. Average stock price was chosen as the dependent variable; average market share, average sales, average net income, average marketing efficiency index, average customer satisfaction, and average trade rating was fixed as the independent variables. To address the third research question, we developed a separate algorithm. This algorithm was modeled using the dashboard parameters as the dependent variables; these parameters include overall performance, market share, sales, net income, marketing efficiency index, customer satisfaction and trade rating. These variables are expressed in percentage terms; average stock price was fixed as the dependent variable.

RESEARCH DESIGN:

Data was sourced from the output of a simulation study-Pharmasim. The data gathered included team performances from 2010 to 2018. The data was split according to terms. We had a total of 24 terms data (Fall, Spring and Summer). We had a total of 277 data points initially, which we further examined for any discrepancies. We found that there were two teams who did not complete the simulation during the period considered for this study. The data from these two teams was removed from the raw data gathered and statistical tests were carried out. To address the research questions, we raised we segmented the teams using cluster analysis technique into three distinct clusters- High Performers, Moderate Performers and Poor Performers.

Teams were segmented into 3 & 4 clusters. We carried out further statistical tests to determine whether there was a statistical difference in the performance of the teams. This was determined using discriminant analysis and MANOVA.

The neural network algorithm was developed using MATLAB. Two separate neural networks were developed- one to predict the average performance parameters, and a second algorithm to predict dashboard effectiveness.

RESULTS AND DISCUSSION:

Teams were segregated into three categories- high performers, moderate performers and poor performers. Cluster analysis was carried out by segregating the teams into 4-clusters and 3-clusters. In each case, the confidence interval was fixed at 95%. The results are shown below. Table 1 shows the classification of teams in case of a four-cluster solution. Table 2 shows the results of the ANOVA conducted in case of a four-cluster solution.

CASE 1: 4-CLUSTER SOLUTION

Number of Cases in each Cluster

Cluster	1	11.000
	2	53.000
	3	128.000
	4	83.000
Valid		275.000

Table 1: Classification of teams- 4-cluster solution

ANOVA

	Cluster		Error			
	Mean Square	df	Mean Square	df	F	Sig.
Overall	53.884	3	1.064	271	50.654	.000
Overall_Std	40.700	3	1.118	271	36.397	.000
AVE_MKT_Shr	188.687	3	.877	271	215.262	.000
AVE_Sales	187871.550	3	341.389	271	550.316	.000
AVE_NI	21867.636	3	172.388	271	126.851	.000
Ave_MEI	.742	3	.098	271	7.543	.000
Ave_Cust_Sat	36.104	3	1.394	271	25.899	.000
Ave_Trade	3.319	3	.084	271	39.557	.000
AVE_MKT_Expense	3020.064	3	28.441	271	106.187	.000
Ave MKTG Expense Per Brand	172.018	3	11.513	271	14.941	.000

Table 2: ANOVA results- 4-cluster solution

4 CLUSTER SOLUTIONS, 95% CONFIDENCE INTERVAL				
PARAMETERS	CLUSTER 1	CLUSTER 2	CLUSTER 3	CLUSTER 4
Overall	98.02%	95.32%	96.78%	97.41%
Overall (Std. deviation)	2.39%	4.45%	3.16%	2.58%
Avg. Market share	28.19%	22.23%	24.18%	25.76%
Avg. Sales	$712.42	$518.09	$573.50	$624.75
Avg. Net Income	$172.11	$114.84	$137.63	$155.53
Avg. Stock price	$117.35	$59.47	$76.26	$91.30
Avg. MEI	$2.32	$2.35	$2.56	$2.56
Avg. Customer Satisfaction	62.05%	60.08%	61.37%	61.83%
Avg. Trade Rating	7.30	6.54	6.70	6.97
Avg. Mkt expense	$74.88	$49.10	$54.13	$61.11
No. of brands	3	2	3	3
Avg. Mkt expense/brand	$24.96	$19.25	$18.59	$20.49

Table 3: Summary of results- 4-cluster solution

Based on the results of table 3, we see that teams in cluster 1 are the high performers (11 teams across the academic period from Fall 2010 to Spring 2018). This is indicated by the highest value in terms of overall percentage mission accomplished, and the lowest value in standard deviation. The low value of standard deviation indicates that these teams were highly consistent in their performances across the 10-year period of the simulation. The teams in this cluster also had the highest market share achieved, highest net income, highest sales volume achieved, highest average stock price, highest average customer satisfaction and highest average trade rating. These teams also spent the most, on an average, on their marketing expenses. However, these teams had the lowest marketing efficiency index (MEI). This indicates that the teams approach to marketing was conservative, i.e. the teams were aware that they were performing very well on the simulation, but they failed to fully capitalize on their strengths.

Referring to table 3, we see that teams in cluster 2 were the poor performers (53 teams considered across the academic period Fall 2010 to Spring 2018). This is indicated by the lowest overall percentage mission accomplished and highest standard deviation. The high standard deviation indicates that these teams were not very consistent in their performances in the simulation. The teams in this cluster also had the lowest market share achieved, lowest net income, lowest sales volume achieved, lowest average stock price, lowest average customer satisfaction and lowest average trade rating. This indicates that the teams in this cluster were reactive in their approach, and were not fully able to understand the consequences of the marketing strategies they adopted. However, they had a relatively higher MEI compared to the teams in cluster 1; this indicates that the teams tried to make best use of the resources available to them; the low MEI indicates that the low returns were due to their poor understanding of marketing strategies.

Teams in clusters 3 & 4 were the moderate performers. When compared to each other, as well as based on an overall comparison, we find that teams in cluster 4 were the closest to the team in cluster 1 in their performance on the simulation. Like the previous cases, we arrived at this inference based on the percentage of mission accomplished, as well as the standard deviation. The low values of standard deviation indicate that the teams were consistent in their performance over the simulation period. Teams in cluster 3 & 4 had the highest MEI. This indicates that the teams were aware of their strengths, and were also aware that they were closer to the teams in cluster 1 in terms of their overall performance on the simulation. The gap in the performance of the teams in cluster 1, and cluster 4 specifically could be attributed to the learning curve- in this case, teams in cluster 4 passed through a learning curve in the simulation, whereas those in cluster 1 intuitively were able to understand how the simulation works. The gap in performances of teams in cluster between could be attributable to this learning curve.

We feel that the most interesting takeaway from the 4-cluster solution pertains to the number of brands managed at the end of the simulation period. We found that the high performers and moderate performers retained all three brands; however, the poor performers tended to drop one of the three brands- in absence of documentary evidence which could provide a definite conclusion on why the teams chose to do so, we hypothesized that the poor performers tended to drop one of the three brands to try and improve their performance on the simulation. We hypothesized that the teams assumed one of the three brands was responsible for their poor performance on the simulation and chose to drop the brand they felt was adversely impacting their performance.

CASE 2: 3-CLUSTER SOLUTION

Like the 4-cluster solution, we also examined the team performances from a 3-cluster solution. Table 4 shows the classification of teams when a 3-cluster solution is considered. Table 5 shows the results of the ANOVA conducted.

Number of Cases in each Cluster

Cluster	1	56.000
	2	136.000
	3	83.000
Valid		275.000

Table 4: Classification of teams 3-cluster solution

ANOVA

	Cluster		Error			
	Mean Square	df	Mean Square	df	F	Sig.
Overall	73.881	2	1.111	272	66.505	.000
Overall_Std	50.330	2	1.193	272	42.190	.000
AVE_MKT_Shr	230.648	2	1.258	272	183.275	.000
AVE_Sales	246306.573	2	601.168	272	409.713	.000
AVE_NI	31747.195	2	179.507	272	176.858	.000
Ave_Stock_Price	21817.797	2	68.215	272	319.837	.000
Ave_MEI	.700	2	.101	272	6.920	.001
Ave_Cust_Sat	50.153	2	1.418	272	35.360	.000
Ave_Trade	3.747	2	.093	272	40.435	.000
AVE_MKT_Expense	4145.254	2	31.166	272	133.005	.000
Ave_MKTG_Expense_Per_Brand	240.287	2	11.602	272	20.712	.000

Table 5: ANOVA results 3-cluster solution

3 CLUSTER SOLUTIONS, 95% CONFIDENCE INTERVAL			
PARAMETERS	CLUSTER 1	CLUSTER 2	CLUSTER 3
Overall	97.59%	97.04%	95.67%
Overall (Std. deviation)	2.54%	2.93%	4.09%
Avg. Market share	26.44%	24.64%	22.77%
Avg. Sales	$651.58	$588.28	$530.86
Avg. Net Income	$163.75	$142.11	$120.58
Avg. Stock price	$99.27	$80.61	$63.37
Avg. MEI	$2.50	$2.57	$2.41
Avg. Customer Satisfaction	61.87%	61.60%	60.38%
Avg. Trade Rating	7.06	6.77	6.59
Avg. Mkt expense	$65.95	$55.59	$50.27
No. of Brands	3	3	3
Avg. Mkt expense/brand	$22.16	$18.92	$18.81

Table 6: Summary of results- 3-cluster solution

Like the 4-cluster solution, we have segregated the teams into three categories- high performers, moderate performers and poor performers. Examining the results from table 6, we see that teams belonging to cluster 1 are the high performers. This is indicated by the highest value in terms of overall percentage of mission accomplished and low standard deviation values. The low standard deviation indicates that teams in this cluster were consistent in their performances on the simulation.

The teams in this cluster also had the highest market share achieved, highest net income, highest sales volume achieved, highest average stock price, highest average customer satisfaction and highest average trade rating. These teams also spent the most, on an average, on their marketing expenses. The difference, compared to the 4-cluster solution is that the teams who are classified as the high performers rank 2nd in terms of their MEI. This indicates the high performers are more efficient in budgeting when their marketing expenses are considered.

Teams in cluster 2 were the moderate performers; they however ranked the highest when MEI is considered. Referring to the table 6, we see that the differences in performance of high performers and moderate performers is minimal; we hypothesize that the moderate performers were aware that they closely lagged the high performers and actively tried to match the performance by utilizing their marketing knowledge; similar to the 4-cluster solution, in the absence of documentary evidence which explained the rationale of the factors affecting teams' decision making, we hypothesized that the difference was due to the learning curve- teams in cluster 1 were intuitively able to understand how the simulation worked, while teams in cluster 2 had to undergo a learning curve to understand how the simulation worked.

Teams in cluster 3 were classified as the poor performers. This was based on the lower overall percentage of mission accomplished and higher standard deviation. The high value of standard deviation indicates that the poor performing teams were not fully able to understand how the simulation worked. The high value of standard deviation also indicated that the teams were not consistent in their performance.

The most interesting takeaway from the 3-cluster solution is that the 3-cluster solution was unable to separate the teams based on the number of brands the teams managed at the end of the simulation period.

After carrying out the cluster analysis, we developed the neural network algorithm. The neural network was developed for two parameters- average performance parameters and dashboard parameters. In both cases, we have considered the average stock price as the dependent variable. In case when the average parameters were considered for developing the neural network, we have considered the average parameters, namely the average market share, average sales, average net income, average MEI, average customer satisfaction average trade rating, number of brands managed and average marketing expense as the independent variables. In the second case, i.e. when the dashboard parameters are considered, we have considered the average stock price as the dependent variable and the dashboard metrics- overall performance, market share, sales, net income, MEI, customer satisfaction, and trade rating as the independent variables.

The rationale for choosing the average stock price as the dependent variable is based on two factors- One, in the absence of knowledge of internal factors which affect decision making, the average stock price is a good metric to understand the performance of the organization. Secondly, when the teams are conducting the simulation every academic term, teams are unaware of the interplay of factors driving other teams' decisions. The only reference point of comparison in such a case, the stock price helps individual teams assess their performance at each period in the simulation. By considering the average value, we also smoothen the result, i.e. the influence of factors which might cause a sharp increase or decrease are negated when the arithmetic mean is considered over a period.

However, in both cases, one important factor is to be kept in mind. The dataset must be randomly divided into two samples; for our study, we named the samples as training set and validation set respectively. The reason is that neural network must be trained before the algorithm can be used to predict the performance parameters. The other important consideration is that the training dataset must contain the lowest and the highest output parameter (in our case, average stock price). This helps the algorithm understand the range of the dataset in consideration.

CASE 1: WHEN THE AVERAGE PERFORMANCE PARAMETERS ARE CONSIDERED

In this case, the average stock price is considered as the dependent variable and the average market share, average sales, average net income, average MEI, average customer satisfaction average trade rating, number of brands managed and average marketing expense as the independent variables. The network is trained with the data samples from the training set. Default configuration is chosen for the neural network; in this configuration, 70% of the samples from the dataset are randomly chosen by the algorithm to be the training sample, 15% of the samples are chosen to validate the model developed and 15% of the samples are chosen to test the model for fit. The network is developed to have 7 hidden layers; this means that 7 iterations are carried out by the algorithm on the whole dataset. In other words, the network developed initiates the learning process and starts developing a model; once the network arrives at the data sample that is unable to be best explained by the model, it automatically tries to understand the gap based on whatever it has already learnt. If no suitable explanation could be developed, the network again initiates the learning process. This is carried out 7 times.

Based on the training model developed, the model provides us with an R-value. The R-value here represents the degree of correlation, i.e. the correlation of the predicted value with the actual value. From figure 1, we see that the correlation is almost perfectly correlated, i.e. for the data samples chosen for training the data set, the degree of correlation between predicted and actual value is found to be 0.994; similarly, the degree of correlation for the validation and testing dataset samples is found to be 0.994 and 0.985 respectively. Figure 2 shows the relationship between actual values of the stock price and the predicted values. Referring to figure 2, we see that the network can predict the average stock price for each team with a very high degree of accuracy. This is reinforced by the high R-value from figure 1. We see that when the overall model is considered, the degree of correlation between the actual and predicted values is found to be 0.993.

The inference in this case is that when we model the neural network based on the average parameters, the neural network can almost perfectly mimic the decision-making abilities of an individual, i.e. given the same marketing knowledge and data that a decision maker has, a well-trained neural network program has the capability of taking decisions which a decision maker who has the similar level of knowledge and access to data would in the given circumstances.

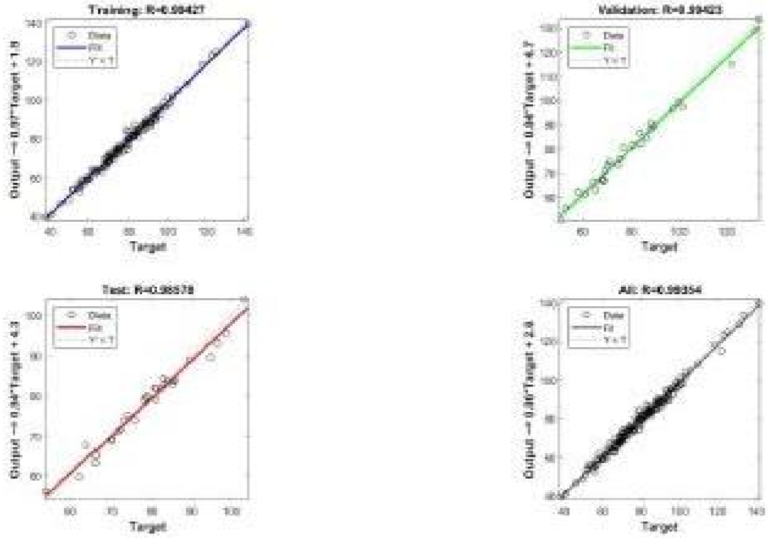

Fig 1: Degree of correlation-training dataset.

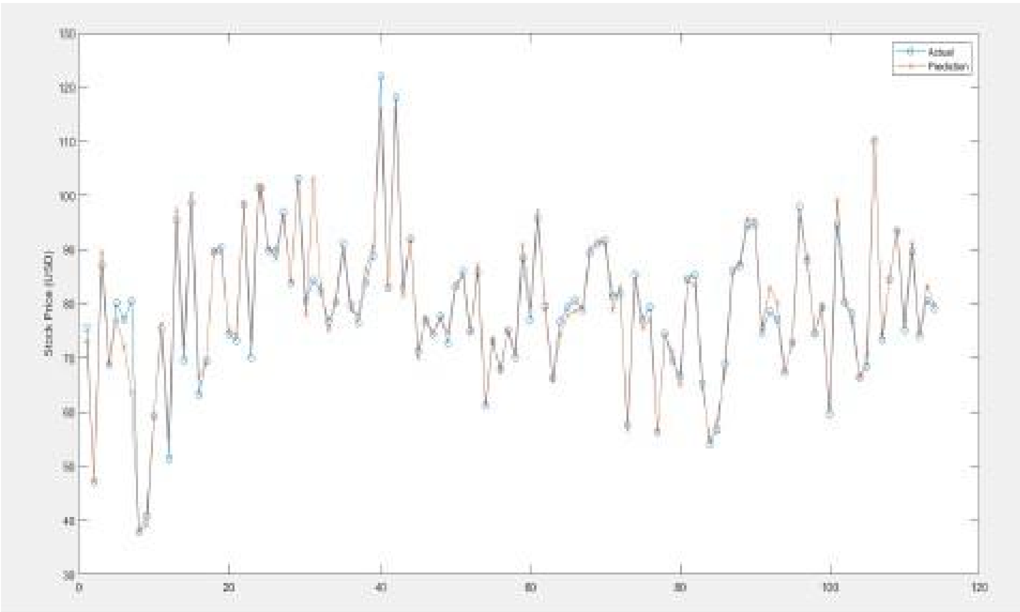

Fig 2: Actual vs. Predicted stock price- Average parameters

CASE 2: WHEN THE DASHBOARD PERFORMANCE PARAMETERS ARE CONSIDERED

In this case, the average stock price is chosen as the dependent variable, and dashboard parameters are chosen as the independent variables; the dashboard parameters are expressed in terms of percentage accomplishment over the 10-year period for which the simulation is considered. These parameters include overall mission accomplished, market share, sales, net income, MEI, customer satisfaction, and trade rating. The network is trained with the data samples from the training set. Default configuration is chosen for the neural network; in this configuration, 70% of the samples from the dataset are randomly chosen by the algorithm to be the training sample, 15% of the samples are chosen to validate the model developed and 15% of the samples are chosen to test the model for fit. In this case, we have developed the network for 5 hidden layers and 7 hidden layers. Figures 3 & 4 show the degree of correlation values for 5 & 7 hidden layers respectively. Like the previous case, we have chosen the default configuration to train the network, i.e. 70% of the samples from the dataset are randomly chosen by the algorithm to be the training sample, 15% of the samples are chosen to validate the model developed and 15% of the samples are chosen to test the model for fit.

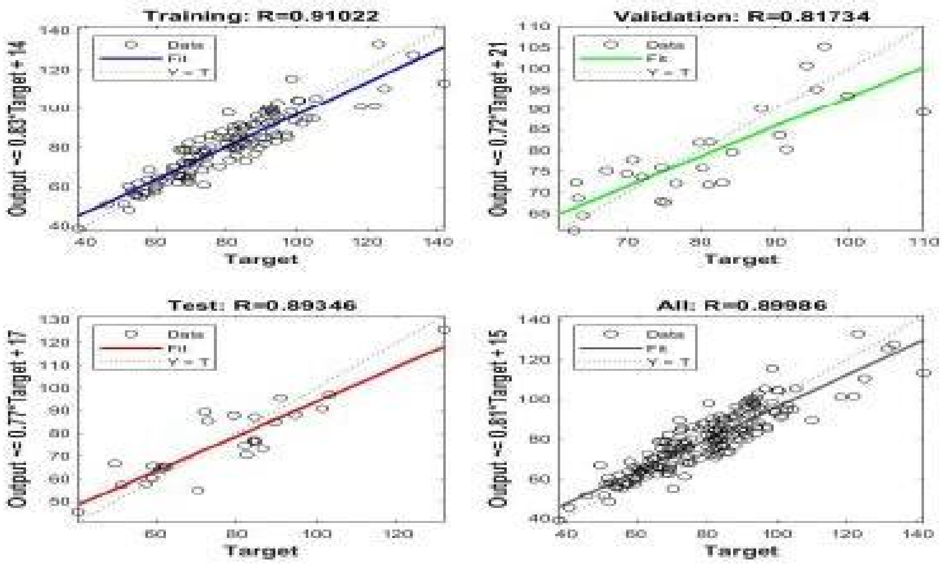

Fig 3: Degree of correlation: 5-layer neural network.

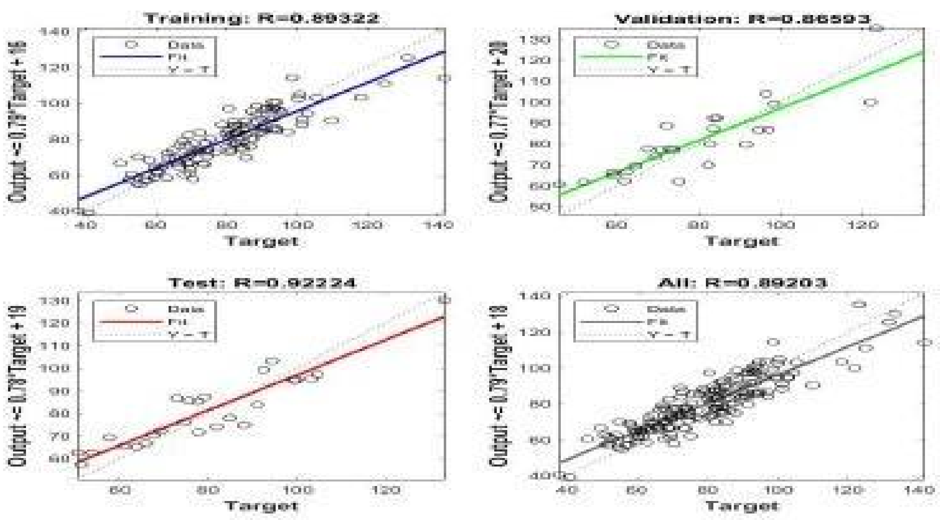

Fig 4: Degree of correlation: 7-layer neural network.

From figures 3 & 4, we see that the degree of correlation is significant; however, in comparison to the case when the network was modeled using the average parameters, the degree of correlation is lesser. Figure 5 shows the relationship between actual values of the stock price and the predicted values. Referring to Fig. 5, we see that the network can predict the average stock price based on the dashboard parameters considered; however, the accuracy is not as high when compared to predicting the average stock price using the average performance parameters.

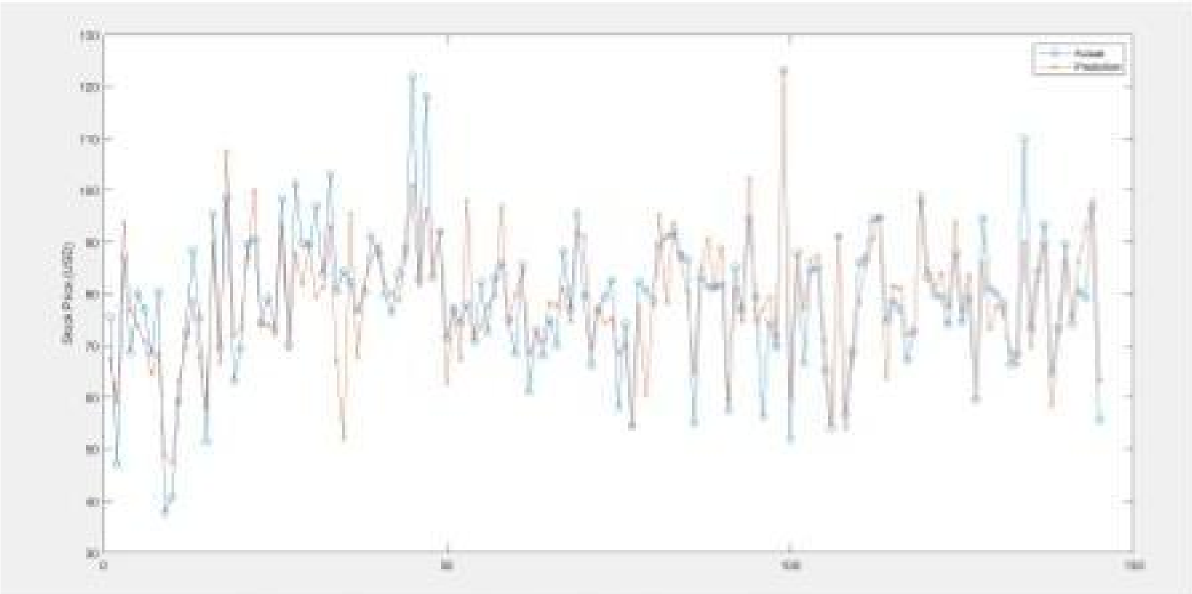

Fig 5: Actual vs. Predicted stock price- Dashboard parameters

The inference in this case is that when we model the neural network based on the dashboard parameters, the neural network can be used to determine the effectiveness of a marketing dashboard.

CONCLUSION

The key takeaways from our study are:

1.) Neural networks can accurately replicate human decision making, when the average performance parameters are considered.

2.) Neural networks can predict the performance parameters, with a high degree of accuracy, when marketing dashboard parameters are considered.

3.) A neural network can be used to measure and predict the effectiveness of a marketing dashboard

Modelling the neural network based on the average parameters, we found that the neural network can mimic the decision-making capabilities of a decision maker in an organization, when it is programmed to have the same level of knowledge and access to data that the decision makers have.

The third research question we addressed was whether a neural network can be used to determine the effectiveness of a marketing dashboard. We found that the neural network can effectively predict the performance of teams based on a marketing dashboard parameter approach.

However, the limitation on our study is that the exercise was conducted on the output results of a simulation study. The simulation is conducted in a controlled environment, free of external factors and all teams are subject to the same constraints, which are independent of external factors that have an impact on actual organizational performance.

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