must satisfy assumptions. Because of these reason, the effectiveness of these methods largely depends on how they satisfy these assumptions and in which way they are developed. For this reason, users experience and expertise are very important for a successful application. On the other hand, neural networks have emerged as an important tool for classification (Zhang, 2000).

The advantages of using neural networks for classification are:

- At Neural networks the focus point is data and with respect to this data, neural networks use self-adaptive methods in order to adjust themselves to the data without any explicit specification of functional or distributional form for the underlying model.
- Neural Networks are universal functional approximators and with this they have the ability to approximate any functions.
- Neural networks are nonlinear models, so it is easier to apply them to real world non-linear models.
- Neural networks can estimate the hidden probabilities, which give them the ability to establish classification rules and perform statistical analysis (Zhang, 2000).

In order to classify with neural networks, data with two parts is used. First part is called input data, which includes attributes that is used for classification. Second part is called target data. Target data gives the real classification results of the samples as binary values. Target values are compared with signals that come from the input and by using the back propagation method; neural networks train themselves and find the best weights.

3 METHODOLOGY

3.1 DEA supported Artificial Neural Network

Below figure illustrates the flow of the application process that starts with data collection and selection, continues with DEA analysis and finishes by ANN classification of SMEs' efficiency.

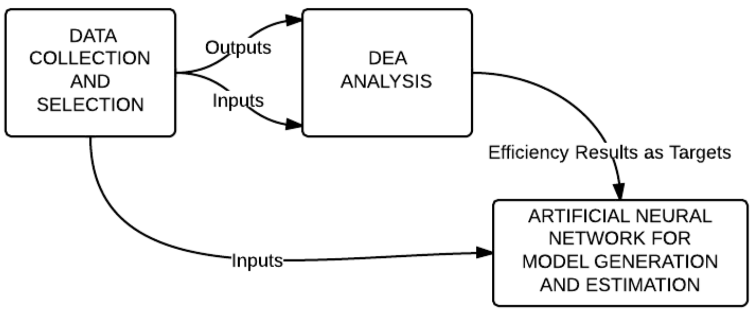


Figure 1: Flowchart of the application

3.2 Data Collection

For this study, data is gathered from 744 manufacturing SMEs from 10 different industries via online survey filled by companies' top managers. Survey questions are written according to proposed model based on a 5 point Likert Scale (1 = very weak to 5 = very strong) except one output called profit margin.

In the proposed model; output oriented CCR model is used, since the objective is to increase efficiency by increasing output levels. The main goal of the proposed model is to figure out whether or not a SME is efficient if the value of the objective function equals 1 or if it is less than 1, it is inefficient.

Input variables are proximity to market with respect to competitors, ability to control costs, potential labor force, product quality, prompt advantage, certification, product assortment, distribution channel, pricing policy, service, capital and machinery-equipment track and output variables are profit margin and market share. All data from 744 companies used in the DEA analysis. In the result of efficiency analysis, there are 94 companies obtained comparatively efficient best practice SMEs (score=1) and 650 inefficient companies (score<1) observed and reference set for each inefficient units are identified.

3.3 Artificial Neural Network Analysis

In this study, SMEs are classified as efficient or not efficient with respect to ANN classification analysis. Data is provided by KOSGEB. The following attributes determined by the DEA application are used as inputs in neural network:

- Proximity to market with respect to competitors
- Ability to control costs
- Potential Labor Force
- Product Quality
- Prompt Advantage Prompt
- Certification
- Product Assortment
- Distribution Channel Power
- Pricing Policy
- Service
- Capital
- Machinery-Equipment Track

The classification results found by the DEA are used as target values. The SMEs data are used in the analysis and it has 744 samples. MATLAB software's Neural Network toolbox is utilized to do the analysis.

12 attributes will enter this model from the input nodes. From there they will flow through the hidden neurons. The number of hidden neurons is 10 as a default in MATLAB, and changing the size of hidden layer size to lower and higher numbers resulted in worse solutions. So, default numbers of hidden layers are used. As an output, the inputs samples will leave the network as either 1 (efficient) or 0 (non-efficient). Generally, sample data are divided into three parts by MATLAB; 70% training, 15% validation and 15% testing. So randomly selected 520 data are used for training the network, 112 data are used for validation and 112 data are used for testing this newly formed network.

When the inputs and targets are entered to the MATLAB's neural network toolbox, the following results are found.

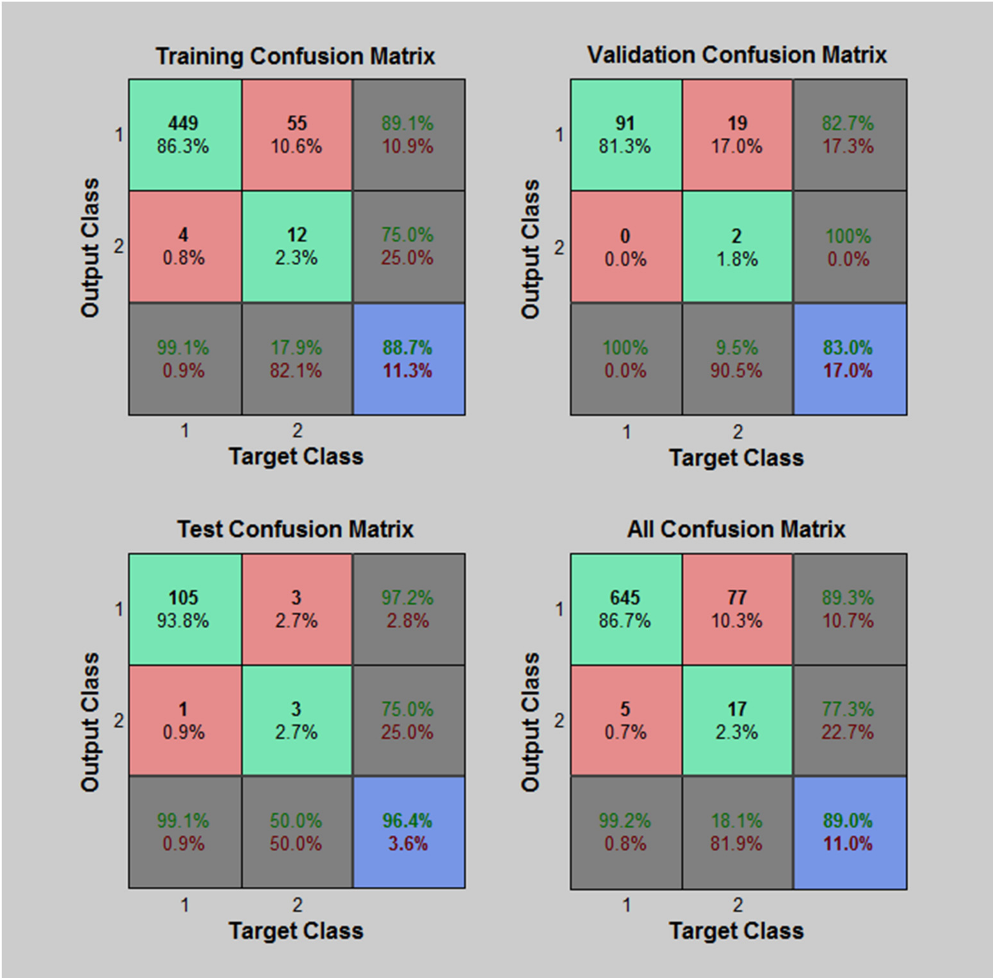
Figure 2: Error Values of Classification

Results

	Samples	MSE	%E
Training:	520	8.90280e-2	11.34615e-0
Validation:	112	1.28008e-1	16.96428e-0
Testing:	112	4.42177e-2	3.57142e-0

When Figure 2 is examined, MSE results and percentages from the classifications can be observed. Neural networks are adjusted with training data, and validation data are used for stopping training before over-fitting. The testing data are independent from both of them and used to measure the performance of the network. Because of that, we will focus of results of the testing data. Error values from the testing of the neural network results the lowest values, which means the neural network is working with an error ratio of is 3.6% and can be interpreted as a well performing model.

Figure 3: Confusion Matrix of Classification



When the confusion matrices in figure 3 are examined, correct, false positive and false negative classifications can be seen clearly. In this figure, the part that needs attention is the classification results of testing. As said before, the testing data is completely independent on training and validation, and shows the real performance of neural network. The detailed explanation of this matrix is in analysis section.

4 RESULTS

From the test confusion matrix classification analysis, all units are observed as efficient and non-efficient. The main evaluation criterion in this model is the performance of the neural network.

Table 1: Test Results of Classification of SME's

	Efficient		Non-Efficient		Total	
Number of SMEs	3	1	105	3	108	4
Performance	75%		97.20%		96.40%	
	False Negative: 25%		False Positive: 2.8%			

In Table 1, in "Number of SMEs" row, the amount on the left side for each column shows the correct classification, and the amount on the right side for each column shows the incorrect classification according to DEA results. The “Performance” row shows the efficiency performance percentages of these classifications.

By examining the efficiency results, some patterns are easily recognized. For efficiency results, neural network model is better in classification of the non-efficient SMEs. The imbalance between number of efficient and non-efficient SME’s causes this pattern. For all data the efficient and non-efficient ratio is 0.145 and because of that neural network model’s false positive and false negative ratios are different. The false negative is the situation in which efficient SMEs are considered non-efficient and false positive is the situation in which non-efficient SMEs are considered efficient. In the model, from the results, it is clearly seen that false positive ratio is smaller than the false negative ratio. In a sense, this is a good result, because this means that the neural network does not classify the non-efficient SMEs as efficient SMEs. Because, if an SME is classified as non-efficient even if it is efficient, it can improve itself to be more efficient, but if a non-efficient SME is classified as efficient, this can result in big damages for the SME.

So to conclude, neural network is trained more at non-efficient results. In future, if new efficient SMEs data is added, then the neural network can be trained to make better efficiency classification.

5 MANAGERIAL IMPLICATIONS AND CONCLUSION

The importance of this study comes from the fact that in real world some outputs are difficult to obtain, especially output values like total sales and market share. Because, these values can be manipulated and take a lot of time and effort to calculate. That is why, a model which only uses easy to find inputs without relying the outputs can be effective in many ways. Also, it consumes less resource and can be applied quickly.

DEA has some shortcomings. First of all, because of the DEA models working principle, when a new sample is added, the model needs to find the results from the start and this will consume additional time. The neural network model just uses the pre-found weights to classify the new sample. Secondly, since the DEA model starts the analysis from the scratch, it will find new results, which can cause some inconsistencies with the previous results. For example, because of the addition of the new sample, a previously efficient sample can be found non-efficient and vice versa. But this shortcoming can be bypassed by using neural network because, again, neural network model just uses the pre-found weights to classify the new sample, the models is not started from the beginning and no new weights are found, so the results are consistent.

This study can be applied into many sectors and has many implementations over the business world. Each efficiency decision that uses other models can be used by this model with lesser attribute. Such as; Credit scoring, supplier selection, self-evaluation, resource allocation and management and etc.

As a future study, when additional data is collected, a more solid neural network model which is stronger on false negative can be form. Also in future, a neural network model which uses fewer inputs can be formed.

To conclude, we formed a neural network with the results taken from the DEA analysis. From the neural network, the classification results are found and their performances are measured. DEA needs two types of data, inputs and outputs in order to make classification. Our aim in this study is to use DEA as a stepping stone to the neural network model and make classification by just using the inputs from DEA. From the results, the target seems to be achieved and new SMEs can be easily classified upon their operational efficiencies with this model.

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