Identification of Determinants for Globalization of SMEs using Multi-Layer Perceptron Neural Networks

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RECEIVED ON 05.01.2015 ACCEPTED ON 28.05.2015

ABSTRACT

SMEs (Small and Medium Sized Enterprises) sector is facing problems relating to implementation of international quality standards. These SMEs need to identify factors affecting business success abroad for intelligent allocation of resources to the process of internationalization. In this paper, MLP NN (Multi-Layer Perceptron Neural Network) has been used for identifying relative importance of key variables related to firm basics, manufacturing, quality inspection labs and level of education in determining the exporting status of Pakistani SMEs. A survey has been conducted for scoring out the pertinent variables in SMEs and coded in MLP NNs. It is found that 'firm registered with OEM (Original Equipment Manufacturer) and 'size of firm' are the most important in determining exporting status of SMEs followed by other variables. For internationalization, the results aid policy makers in formulating strategies.

Key Words: Exporting Status, Globalization, Internationalization, Multi-Layer Perceptron, Neural Network, Small and Medium-Sized Enterprises.

1. INTRODUCTION

SMEs have net sales lower than Rs. 300 million in accordance with the most recent financial statements [1]. Firms having less than 36 employees are regarded as small sized firms; those having 36 or more employees are regarded as medium sized firms [2]. According to Census of Establishments 2005, from the private industry of Pakistan, almost 90% consists on SMEs and approximately 78% of workforce is employed. Pakistani SMEs are not well-organized, have slow growth rate and only 4% are able to survive beyond 25 years [3]. Khattak, et. al. [4] evaluated that SMEs contribution in the annual GDP is 40%. Mature multinational corporations are found playing a dominant role in previous international business literature. Internationalization of SME's has recently achieved broader interest [5]. There exist three models for explaining the internationalization process vise; stage or sequential internationalization model, TCA (Transaction Cost Approach) and network approach. Stage model is also called Uppsala model. It explains that firms increase their commitment towards internationalization as their market knowledge and experience grows as shown in Fig. 1.

Transaction costs include market entry costs in international markets. TCA suggests that the firm's choice should be done on the basis of costs of transactions and conditions underlying market failure. Under this approach,

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for example, search costs for a market in close proximity will be lower and more acceptable than those for a market beyond. Osarenkhoe [6] argued that at internationalization environment, a firm cannot be accessed as solo entity; rather it should be viewed in comparison with its competitors and specially the small firm with its ties with other firms.

SMEs' internationalization has been studied intensively with reference to factors both in internal and external environment of SMEs by researchers all over the world. Ultimate focal point of researchers has been the development of recommendations for governments and SMEs promising successful export activities of target firms. Development in SMEs sector requires identifying, exploring and resolving the problems faced by SMEs export sector, since exporting is a complicated and expensive decision. A set of serious constraints in this regard includes the size of the firm, restricted economics, technical and labor resources, and less exposure to global marketplace and other constraints caused by time and distance. An accurate method like MLP NN has been used for the internationalization of the SMEs. Next section review the literature followed by the mathematical model, methodology and result.

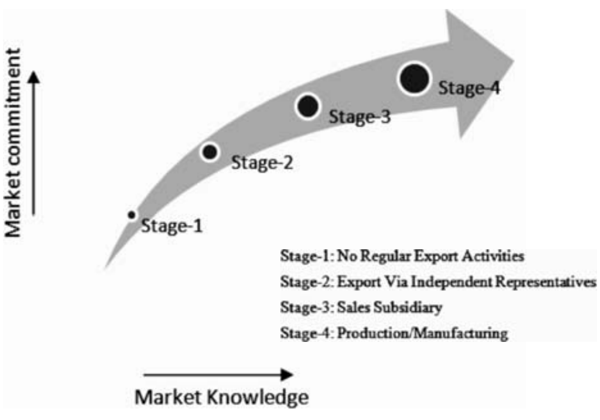

FIG. 1. FOUR STAGES OF INTERNATIONALIZATION [6]

2. LITERATURE REVIEW

Voges and Pulakanam [7] investigated that the efficient use of internet technologies can resolve most of problems associated with SMEs. Another powerful tool for alleviating such constraints and securing SMEs' survival and growth is the development of effective 'functional networks'. These networks include: discussion, information, consultancy, poignant support and resource possession networks [8]. SME's pro-activeness to operate in international markets through innovative products is measured as EEO (Export Entrepreneurial Orientation) and has been found to demonstrate positive significant relation with firm's overall outcome of export activities (in terms of ultimate profits, sales, market share, competitiveness and customer satisfaction) measured as EP (Export Performance).

Godwin and Abaho [9] emphasized that SMEs must create and promote a culture that encourages pro-activeness and innovation to achieve a winning position in overseas market. Lim and Kimura [10] had revealed that SMEs can benefit from GVCs (Global Value Chains) by supporting the lead firm in the tiered structure shown in Fig. 2. First entry is generally at lower tier level but this position is unstable and can easily be replaced by other suppliers. SMEs therefore, need to move up this tier by enhancing value content of their part of activities. Bhatti and Awais [11] argued that entrepreneurial motivation and willingness to operate in international market largely determines the exporting status of the SMEs. It is recognized that influential factors contributing to internationalization of Malaysian SMEs (arranged in descending order) include industrial networking, firm specific, industrial, external and motivational factors by [12].

Internationalization of Pakistani SMEs has also been a point of interest for researchers. Akhtar, et. al. [13] conducted their research with reference to SMEs in Sialkot operating in supports, surgical equipments and leather goods, a positive correlation has been found between location, firm and managerial specific factors and the firm's foreign market performance. Authors [4] found that external exporting barriers constitute 32% and internal barriers make up 68% of total barriers to internationalization of Pakistani SMEs. Internal barriers include energy crisis, functional, environmental and marketing. The prioritization has been done based on the key performance indicators of manufacturing firms based on the volume and variety of the products [14-15]. External barriers include competition from countries like China, India and Bangladesh, procedural like documentation, quality clearance, and late payments etc. and environmental such as unstable political situation, cultural effects and economic problems. PLS-PM (Partial Least Squares Path Modeling) technique used in the same context concluding that enterprise and quality level factors exercise high influence reported by [16]. Researchers [2] employed the discriminant analysis technique to investigate organizational parameters

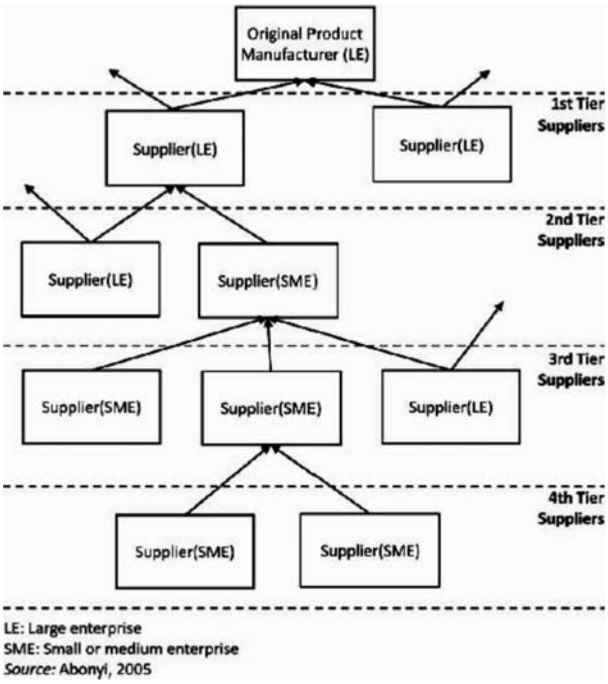

FIG. 2. HOW SMES FIT INTO GLOBAL VALUE CHAINS [10]

determining capability of Pakistani SMEs in accomplishing successful foreign business. In OECD Conference [17] it was recognized that the use of quality assurance tools and education level of both technical and management teams found important in determining this capability. Jahanzaib and Akhtar [18] advocated for technology driven strategy for the industrialization. Finally, internationalization of SMEs requires dynamic cooperation among the classified sector, governments and at international level firms. Witten and Frank [19] recognized that NN develops hyper-planes (called perceptrons) to classify the data. Another name for NN learning is 'connectionist learning' because of this massive interconnection as identified by [20]. Mitchell [21] stated that the NN have outstanding capability to develop connotation from complex or vague statistics. NN could be utilized to dig out patterns and distinguish trends that are much difficult to be traced by either humans or through other techniques (Fig. 3).

Schalkoff [22] exposed that the utilization of NNs, and specially the MLP proved to be more successful alternative as compared to the conventional numerical techniques. Yan, et. al. [23] claimed that MDSS (Medical Decision

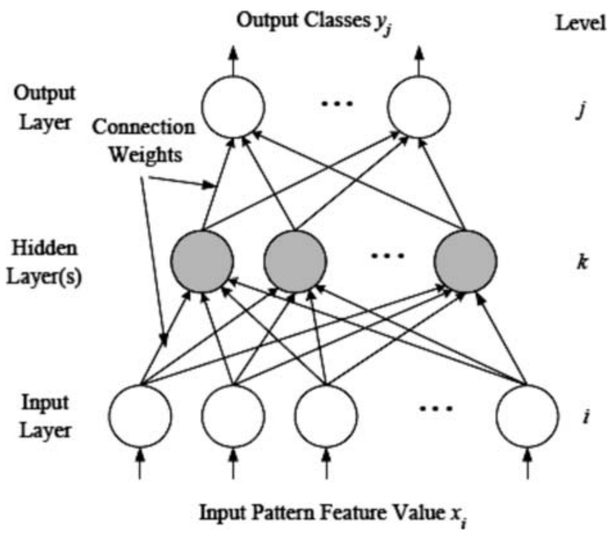

FIG. 3. ARCHITECTURE OF MLP NEURAL NETWORK [21]

Support System) exploits the MLP for cardiology malady identification. Other applications include predicting the maximum shear capacity of RC (Reinforced Concrete) beams evaluated by [24], the use of active control in flight trailing of mobile robots was reported by [25], estimation of crops yield in the coming year was accessed by [26], dynamic modeling of STLF (Short Term (electrical) Load Forecasting) was developed by [27].

However, accurate mapping of all these factors in determination of exporting status of SMEs requires a technique capable of making universal approximation, dealing with non-linear relations and fault tolerance, all of which are characteristics of real world data. NNs possess all these qualities [28]. MLP NN had been used as research technique for current research. NN technique is inspired from human and animal brains capable of performing complicated tasks involving classification tasks, like image and sound recognition. A single neuron cannot accomplish this task, rather massive interconnection between entire set of these neurons makes it possible.

3. ARCHITECTURE OF MLP

The MLP network may be regarded as a relation of one or more inputs (predictors or autonomous variables) who tends to minimize the forecasted inaccuracies in calculation of output (objective variables). Both input and output variables can be categorical, scale or a mix of two. Notations used for mathematical computation are given below:

M = Total number of patterns / instances, m= 1 , …. , M

P = Number of input variables

R = Number of output variables

I = Total number of layers excluding input layer

J_i = Number of units in layer i

J_o = Number of units in input layer (input layer is called 'zero layer')

J_I = Number of units in output layer

T_c = Set of categorical outputs

T_h = Set of sub-vectors of $y^{(m)}$ containing 1-of-c coded h[th] categorical variable

$X^{(m)} = (x^{(m)}_1,\ldots,x^{(m)}_P)$ = Input vector for pattern 'm'

$Y^{(m)} = (y^{(m)}_1,\ldots,y^{(m)}_R)$ = Output vector for pattern 'm'

$a^m_{i:j}$ = Unit j of layer i, pattern m, j = 0, …. , J_i;i=0,…,I.

$w_{i:j,k}$ = Weight emanating from layer i-l, unit j to layer i, unit k.

$$c^m_{i:k} = \sum_{j=0}^{n_{i-1}} w_{i:j,k} a^m_{i-1:j}, i = 1,\ldots, I$$

$\gamma_i(c)$ = Activation functions for layer i.

W = Weight vector having all weights, i.e. $(w_{1:0,1}, w_{1:0,2},\ldots,w_{I:JI-1}, J_1)$

Input Layer: input layer is regarded as zero layer

J_o = P units, i.e. $a_{0:i},\ldots,a_{0:J0}$

$a_{0:j} = x_j$

i[th] Hidden Layer: has J_i number of units viz; $a_{i:i},\ldots,a_{i:Ji}$

Where, $a_{i:k} = \gamma_i(c_{i:k})$, and i=1,…,I and $a_{i-1:0}$=1

That is, the unit in the next layer 'k' (i.e. $a_{i:k}$) is achieved by first multiplying value of weight ($w_{i:j,k}$) connecting this unit with previous layer unit (shown in Fig. 4) with value of previous unit ($a_{i-1:j}$) and applying summation to get $c_{i:k}$, i.e.

$$c_{i:k} = \sum_{j=0}^{J_{i-1}} w_{i:j,k} a_{i-1:j}$$

And then applying activation function 'γ' on $c_{i:k}$, i.e. $\gamma_i(c_{i:k})$.

Output Layer: has J_I = R units, i.e. $a_{I:1},\ldots,a_{I:jI}$

Where, $a_{I:k} = \gamma_I(c_{I:k})$ and

$$c_{I:k} = \sum_{j=0}^{J_I} w_{I:j,k} a_{i-1:j}$$

i = 1, …… , I and $a_{i-1:0}$ = 1

4. EXPERIMENTAL DESIGN

Experimental design method consists of learning through a series of activities and making conclusions about a process, data generation from the process by performing experiments and updating previous conclusions using data and this process goes on. Engineering design uses experimental design method during product development and improvement like identification of determinants of product performance among various product design parameters. The experimental design method used for this research is termed as 'characterizing' or 'screening' experiment, since this paper is aimed at identifying influential factors in determining the exporting status of SMEs. In other words, emphasis has been on screening or characterizing factors (input variables) exercising high influence on the exporting behavior (output variable). Input variables have been obtained from the literature reported by [2,13,16]. All input/output variables are coded as given in Table 1.

The work is aimed at finding which input variables listed above is significant in determining the exporting status of Pakistani SMEs, so exporting status has been taken as output variable coded as 'Exp_stat'. SMEs fall in three mutually exclusive categories regarding exporting status found by [2, 16]:

(a) Pure Exporting Firms

(b) Pure Domestic Firms

(c) Both Exporting and Domestic Firms

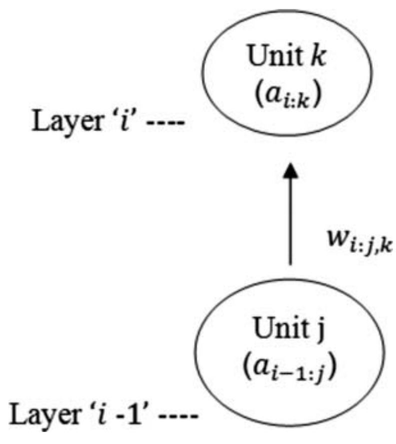

FIG. 4. ILLUSTRATION OF NOTATIONS

5. METHOD OF ANALYSIS

Finalized data set with 13 input variables and exporting status as the output variable has been presented to statistical software (IBM SPSS Statistics Version 20) capable of applying MLP neural network on this dataset to achieve a matrix of relative importance of input variables in determining exporting status of SMEs. Automatic architecture for determining the network structure has been used which selects the best architecture automatically. A sample of coding of variable name, type, and value measurement level involved is given in Table 2.

TABLE 1. DETAIL OF INPUT VARIABLES

No.	Variable Name	Codification
1	Manufacturing Technology	Manuf_tech
2	Automation Ranking	Auto_rnk
3	Origin of Raw Materials	Org_raw
4	Production Personnel Education	Per_edu
5	QA Department Operative	QAD_oper
6	Inspection Lab Operative	Inslb_oper
7	International QA Certification	QA_cer
8	Ranking of Inspection Lab	Rnk_inslb
9	Entrepreneur Education Level	Ent_edu
10	Size of Firm	Frm_size
11	Manufacturing Component/ Assembly/Both/ Processing	Comp_assem
12	Firm Registered with OEM*	Reg_OEM
13	Cluster Membership of Firm	Mem_clst
*OEM refers to the company that originally manufactured the product.		

5.1 Model with Two Samples

Initial MLP model has been developed by dividing SME's population into random samples of training and holdout with training sample consisting of 70% of population SMEs, leaving the rest of 30% to authenticate the investigation (holdout sample) using Bernoulli distribution. This has been accomplished by using a partition variable i.e. '2*rv.bernoulli (0.7)-1'. This partition variable divides dataset such that 70% cases take value +1 (training sample) and 30% take value-1 (holdout sample). Exporting Status [Exp_stat] has been selected as 'dependent' variable (output) and all coded input variables listed in Table 1 have been entered as 'factors'. Tables 3-9 presents the case summary, model evaluation and classification details.

In Table 3 'N' is the number of instances or cases included. Training sample has been assigned 68 cases which constitutes 65.4% of population, while holdout sample has been assigned 36 cases (34.6% of population).Out of a population of 132 cases, 104 are valid cases and 28 cases (having user defined missing values) are excluded.

Table 4 presents the data about outcome of training and implementation of final network to the holdout sample. Estimation algorithm stopped because relative change in training error criterion equal to 0.0001 has been achieved. Percent incorrect predictions for training sample are quite few (2.9%) as opposed to holdout sample having 38.9% incorrect predictions. This drastic imbalance between two samples suggests that training sample has been over trained.

Classification (Table 5) shows percent correct of each category in each sample. Highlighted values along diagonal line are correct predictions for training sample. Again it is evident that the NN developed above has a greater percentage of right cases in the 'training sample' (97.1 % overall percent correct), and the 'holdout sample' performed a substantially inferior job (61.1% overall percent correct). It signifies that the network has been **'over trained'.**

This complication is solved by specifying a fraction of the 'training sample' and re-assigning it to a 'testing sample' to maintain the network on track.

5.2 Model with Three Samples

Random assignment of cases to training, testing and holdout samples has been accomplished by using partition

TABLE 3. SUMMARY OF CASE PROCESSING

		N	Percentage
Samples	Hold-Out	36	34.6
	Training	68	65.4
Suitable		104	100
Disqualified		28	
Total		132	

TABLE 4. SUMMARY OF MODEL

Training	Entropy of Cross Error	5.258
	Incorrect Percentage of Forecasts	2.9%
	Rule Used for Stopping	Achieved relative change in error criterion for training (0.0001) achieved
	Time of Training	0:00:00.05
Holdout	Incorrect Percentage of Forecasts	38.9%

TABLE 2.

Name	Type	Label	Values	Missing	Measure	Role
Manuf_tech	Numeric	Manufacturing Technology	1 = Low (Local) 2 = Medium (Local & Imported) 3 = High (Imported) 9 = Missing	9	Ordinal	Input

variable '*partition-rv.bernoulli(0.2)*' using cases with partition>0. Having done this, the value of partition has been reset which was greater than 0 (i.e. training sample) as a result 20% will get the value 0 (testing sample), the remaining 80% would get the value +1 (training sample). It means 80% out of 70% of original data initially assigned to 'training sample' is the new 'training sample', i.e. 100*(0.8*0.7) = 56% (of original cases).

Remaining cases (14% of original cases) will be in the 'testing sample' while cases assigned to the 'holdout sample' remain intact. After incorporating these changes, *MLP Neural Network* has been run again. All tables, that follow bear '*' sign which shows that these tables are created by dividing population into training, testing and holdout samples. For new configuration of three samples, 54 cases are allocated to training sample, 14 to testing and 36 remain with holdout unchanged. Model summary in Table 6 shows that percent incorrect predictions are now distributed among training, testing and holdout samples. This recommends that the model developed previously using training and holdout samples might be 'over trained' and now the issue has been resolved by inserting a testing sample. Table 6 also shows number of neurons/units in input, hidden and output layers with activation function used in developed model.

Holdout sample provides a measure of overall model accuracy since this sample has not been used in any way in the creation of model. Overall model accuracy is **69.4%** (shown as bold in Table 7).

Fig. 5 shows variation of model accuracy (% correct in holdout sample) with number of epochs. Graph has been drawn by varying number of epochs and simulating model each time and recording the model accuracy. Execution of model training stopped for No. of epochs less than 52 because value of dependent variable was found constant in training sample. For 52 Epochs, % correct is 100% and it falls down as diversity of data (number of epochs) rises. Amplitude of accuracy variation also gets stable with increasing number of epochs. For 132 epochs, model accuracy is 78.1%. Accuracy of previously developed model was 69.4% (Table 7). Thus there is a difference of 8.7% between accuracies of two models.

Comparing classification results with two and three samples (Table 5 and Table 7 respectively); drastic difference between overall percent correct of two samples in Table 5 (97 and 61%) has been controlled by adding a third sample (Table 7). Overall percent correct are now 85.2, 85.7 and 63.6% for three samples. That is how testing sample controls overtraining of network.

TABLE 5. CLASSIFICATION

Sample	Observed	Predicted			
		Exporting	No Exporting	Expo/ Domestic	Percent Correct (%)
Training	Exporting	4	0	0	100.0
	No Exporting	0	42	2	95.5
	Expo/Domestic	0	0	20	100.0
	Overall Percent	5.9%	61.8%	32.4%	97.1
Holdout	Exporting	1	0	0	100.0
	No Exporting	5	13	6	54.2
	Expo/Domestic	1	2	8	72.7
	Overall Percent	19.4%	41.7%	38.9%	61.1

TABLE 6. SUMMARY OF MODEL*

Training	Entropy of Cross Error	26.360
	Incorrect Percentage of Forecasts	14.8%
	Rule Used for Stopping	No decrease in error with 1 consecutive step(s)
	Time of Training	0:00:00.05
Testing	Entropy of Cross Error	5.205
	Incorrect Percentage of Forecasts	14.3%
Holdout	Incorrect Percentage of Forecasts	30.6%
Input Layer	Number of Units	38
Hidden Layer(s)	Number of Hidden Layers	1
	Number of Units in Hidden Layer	1
	Activation Function	Hyperbolic tangent
Output Layer	Number of Units	3
	Activation Function	Soft-max
	Error Function	Cross-entropy

TABLE 7. CLASSIFICATION*

Sample	Observed	Predicted			
		Exporting	No Exporting	Expo/ Domestic	Percent Correct (%)
Training	Exporting	0	1	3	0.0
	No Exporting	0	29	4	87.9
	Expo/Domestic	0	0	17	100.0
	Overall Percent	0.0%	55.6%	44.4%	85.2
Holdout	Exporting	0	0	0	0.0
	No Exporting	0	10	1	90.9
	Expo/Domestic	0	1	2	66.7
	Overall Percent	0.0%	78.6%	21.4%	85.7
Holdout	Exporting	0	1	0	0.0
	No Exporting	0	18	6	75.0
	Expo/Domestic	0	4	7	63.6
	Overall Percent	0.0%	63.9%	36.1%	69.4

5.3 Model Accuracy

Predicted-by-observed chart and ROC curves demonstrate visual display of model accuracy. With reference to predicted-by-observed chart in Fig. 6, the small column at leftmost shows those cases which have got category 'Exporting', the forecasted pseudo-probability of class 'Exporting'. Moving to right, the next column indicates 'No Exporting'. The parts of column above the 0.5 value on the Y-axis correspond to correct predictions shown in the classification Table 7. The part below 0.5 values indicates wrong predictions. Since from Table 7, the model was good at classifying 'No Exporting' and 'Expo/Domestic' and worse on 'Exporting', box plot showing probability of correct classification for 'Exporting' category (first box on left hand side) lies below 0.5 probability line. Box plot showing probability of correct classification for 'No Exporting' category (fifth box from left hand side) is above 0.5 probability line except some outlying cases displayed as 'shaded circle' and '*'. Same is true for 'Expo/Domestic' category for ninth box from left.

One ROC curve is created for each class of output variable based on pseudo probabilities (Fig. 7). 'Sensitivity' is right positive rate and constructed by the side of Y-axis while '1-specificity' is wrong positive rate constructed by the side of X-axis. Initially true positives are encountered as it moves down the ranked list of probability. Subsequently, as it moves further down this list, it is identified that fewer and fewer true positives with more and more false positives and the curve becomes more horizontal.

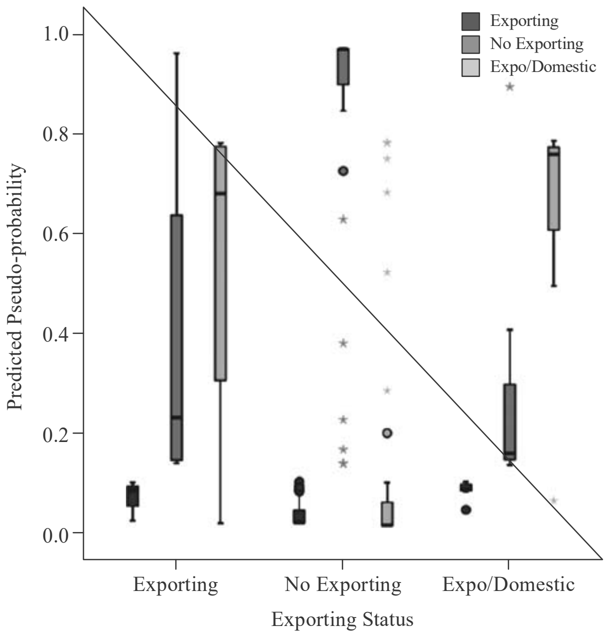

*FIG. 6. PREDICTED-BY-OBSERVED CHART**

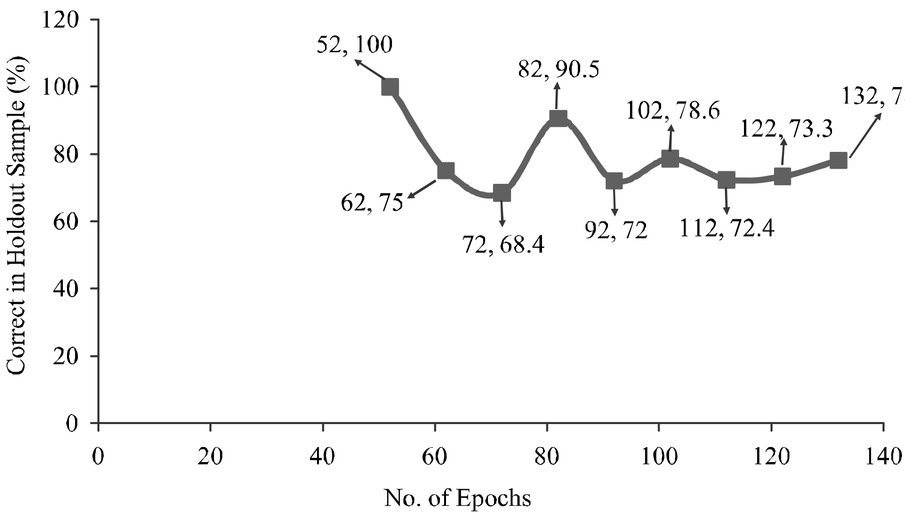

*FIG. 5. NO. OF EPOCHS VERSUS MODEL ACCURACY*3*

Diagonal line represents a situation where it is equally likely to find a true positive or a false positive so curve of an accurate classifier will be farthest from this line in upper part of graph. 'No Expo' and 'Expo/Domestic' curves rise steeply along Y-axis (true positive rate) and have minimum shift along X-axis (false positive rate). Secondly, both of these curves are farthest (as opposed to 'Exporting') from diagonal line. These two factors signify that the model predicts these classes most accurately. This is further confirmed by 'area under the curve' (Table 8).

Closer the area under the curve to '1', more accurate the model is. On the other hand, closer the area to '0.5', less accurate the model is. 'No Expo' and 'Expo/Domestic' curves have areas 0.922 and 0.940 respectively, both being

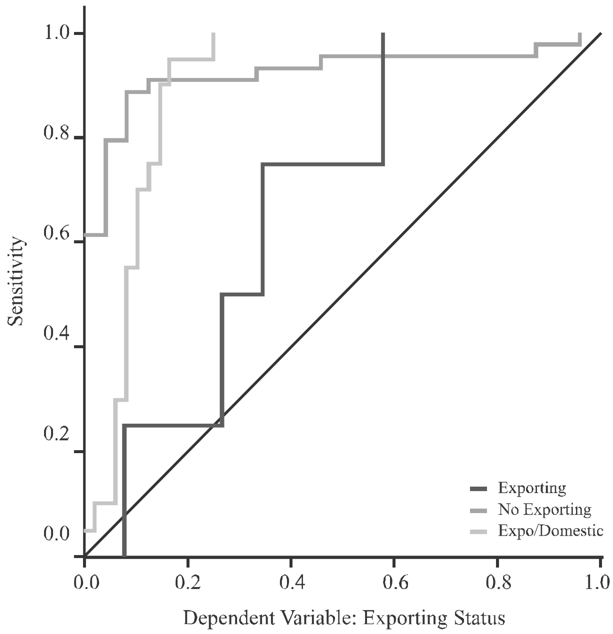

*FIG. 7. ROC CURVE**

TABLE 8. AREA UNDER THE CURVE*

		Area
Exporting status	Exporting	0.684
	No Exporting	0.922
	Expo/Domestic	0.940

closer to 1 show the high accuracy of model in predicting these classes. 'Exporting' class has area = 0.684 which is closer to 0.5 meaning that model is less accurate for this class.

5.4 Sensitivity Analysis

Sensitivity analysis expressed as 'Independent variable importance' analysis computes importance of each independent/input variable. The significance of an input variable is to quantify that how good the network's model forecasted rate changes for diverse values of the input changeable. The analysis is stood on mutual training and testing of samples. Normalized significance of a predictor is calculated as a percentage of maximum value of importance (0.135 for 'Firm Registered with OEM' shown as grey text in Table 9).

The significance of variables chart* (Fig. 8) is simply a bar chart of figures in the importance table. On bottom X- axis are importance's values while on top X-axis are normalized importance values. On Y-axis are different independent variables, sorted in descending order of importance. Fig. 8 represents that the outcomes are governed by firm's registration with OEM, followed by size of firm and origin of raw materials, and followed by other predictors. No factor is less important than 20%.

6. DISCUSSION

MLP NN has been used on dataset of Pakistani SMEs to ascertain importance of each input variable in determining the exporting status of SMEs. Initial MLP model has been developed using training and holdout samples to analyze the importance of various players in SME internationalization. It has been found that network so developed has a greater percentage of acceptable cases in training section as opposed to holdout section (overtraining). Consequently another network has been developed by dividing SMEs' population into training, testing and holdout samples. Overall model accuracy has been found to be **69.4%**. Results displayed in "Significance of Variables" chart may be divided in three categories. High impact variables include those related to firm (Registration with *OEM and size of firm), production and quality (origin of raw materials, international QA certification, manufacturing technology), medium impact variables include* manufacturing component/assembly/both, cluster membership of firm, ranking of inspection lab and production personnel education while low impact variables include automation ranking, entrepreneur education level, inspection lab operative and QA department operative.

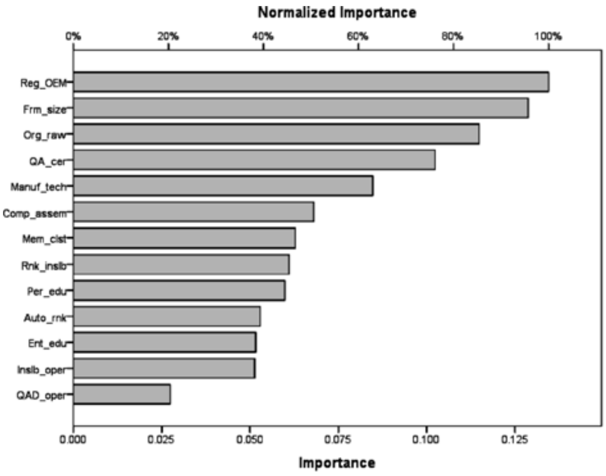

*FIG. 8. SIGNIFICANCE OF VARIABLES CHART**

7. CONCLUSIONS

From the ongoing discussion, following conclusions have been drawn:

(i) Firm Registered with OEMs has been found to be the most influential determinant for the globalization of population SMEs. SMEs have a better access to information regarding documentation, quality standards, key suppliers and expertise required to compete in overseas markets.

TABLE 9. INDEPENDENT VARIABLE IMPORTANCE TABLE*

Input Variable Name		Importance	Normalized Importance (%)
Manufacturing Technology		0.085	63.0
Automation Ranking		0.053	39.3
Origin of Raw materials		0.115	85.4
Production Personnel Education		0.060	44.5
QA Department Operative		0.027	20.4
Inspection Lab operative		0.051	38.1
International QA Certification		0.102	76.1
Ranking of Inspection Lab		0.061	45.4
Entrepreneur Education Level		0.052	38.4
Size of Firm		0.129	95.7
Manufacturing Component/Assembly or Both		0.068	50.6
Firm Registered with OEM		0.135	100.0
Cluster Membership of Firm		0.063	46.7

(ii) Firm size is an important measure of the tendency to export since bigger the firm, superior the limp in decision-making and economic resources and manufacturing capability allowing larger firms to deliver greater prospective to export than their minor counterparts. Likewise, firm size shows available resources like economic and human resource potential which accumulate export information in different forms enhancing the possibility of globalization.

(iii) Association of firm with industrial clusters facilitates internationalization of SMEs in a number of ways like fixed costs of interventions regarding quality up-gradation programs, marketing promotions through foreign missions and fairs and creation of export consortia are distributed among a large number of member SMEs. Other benefits include better occupation among miniature firms, chances for financial system of scale, enhanced productivity, innovativeness and joint design possibilities.

(iv) Higher ranking of inspection lab obviously improves product quality and performance in overseas markets.

(v) Magnitudes of impact of education of both production personnel and entrepreneur have been found in close approximation (44 and 38% normalized importance respectively) meaning that education of both production personnel and entrepreneur is equally important for SMEs' successful globalization.

(vi) Automation ranking (use of manual/automated machines) is a variable of low importance meaning that SMEs using manual and CNC machines have equal opportunity for internationalization.

(vii) Variables 'inspection labs operative' and 'QA department operative' have already been reflected in other variables (obviously SMEs whose ranking of inspection lab is present in the data have their inspection labs operative. Similarly SMEs having international QA certifications mostly have their QA department operative). Consequently 'inspection lab operative' and 'QA department operative' have been found least important in determining exporting status of population SMEs.

8. FUTURE WORK

Future research may focus on Variables in external environment pertinent to present Pakistani scenario like political instability, energy crisis, law and order situation, government regulations, export promotion programs, transport infrastructure, repute in foreign markets and bureaucratic hurdles may also be incorporated. Pakistani SMEs operating in service sector may also be studied for internationalization characteristics specific to service sector internationalization. Finally, internationalization patterns of Pakistani SMEs may be correlated with internationalization models already discussed.

ACKNOWLEDGEMENTS

The authors of this research work are very thankful for the assistance provided by the university staff, especially the University of Engineering & Technology, Taxila, Pakistan, Library staff at every step of this research. Management and other key employees of the selected companies should also be thanked for sparing time to fill up the questionnaire presented to them.

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