Predicting Freshmen Engineering Students Success Using Artificial Neural Network (ANN) Based Emotional Intelligence (EI) Model

Kenneth Nix   Guadalupe Fernandez   Chad Jurica
Laura Lopez   Ranjeet Agarwala   Robert A. Mclauchlan

Department of Mechanical and Industrial Engineering
Texas A&M University-Kingsville

Abstract

Emotional skills are key to personal happiness, healthy relationships, and personally meaningful careers. This paper investigates sensitivity analysis of key Emotional Intelligence (EI) indicators used in an Artificial Neural Network (ANN) for predicting freshmen students' success in Engineering. In this paper three different ANN architectures are compared along with relative weights of key EI indicators. The contribution of EI indictors and the ability of each ANN model with respect to student success are determined. Outcome is measured through key problem areas which, when overcome can serve as a platform to foster high levels of academic achievement.

Introduction

There has been a growing interest in the prediction of the academic success for students. Studies have shown that IQ alone is the only factor contributing to the academic success of students. As a matter of fact, recent studies show that IQ only contributes 20% while emotional intelligence (EI) contributes the rest. Emotional intelligence is defined as: being able to monitor our own and other's feelings and emotions, to discriminate among them, and to use this to guide our thinking and actions. Emotional Intelligence reflects one's ability to deal with daily environmental challenges and help predict one' success in life, including professional and personal pursuits. Emotional Intelligence is a new concept, but it can be as powerful as IQ and sometimes even more. Unlike IQ, we can teach and improve in students some important emotional competencies. Emotionally intelligent people are more likely to succeed in everything they undertake. Teaching emotional skills are very important at school because it can affect academic achievement positively during the year they are taught as well subsequent years.

Prior researches on engineering student success have concentrated on statistical models. French, Immekus and Oakes[1] examined a model of student success and persistence at two levels: university and engineering. This model, based on theoretical and empirical evidence, included both cognitive and noncognitive factors. Through the use of path analysis, several significant relationships among the factors were found. Furnham, Premuzic and McDougall[2] in their research have explored the relationship between big five personality traits, cognitive ability, and beliefs about intelligence (BAI) in a longitudinal study using a sample (N = 93) of British university students. The three sets of variables were used to predict academic performance (AP) (i.e., examination grades) as well as seminar performance (i.e., behavior in class, essay marks, and attendance record) aggregated over a 2-year period. Correlational analyses showed that personality (but not intelligence) was related to BAI (specifically entity vs. incremental beliefs).

This paper is based on a survey[3] given to a freshman engineering students. The survey provides students with a self-assessment tool of current development levels. Students were asked to complete emotional skills assessment profile to gain valuable personal information about themselves and their emotional skills. The data was used to predict the overall success of student using neural networks, over three potential problem areas of life, which a person would need to overcome to foster academic success.

Emotional Intelligence Model

The emotional intelligence model was based on a survey[3], which was divided into four parts, with each part containing its own sub category. Part 1 was titled Interpersonal Communication under Stress and dealt with three key emotional skills. These skills were: assertion, anger control and management, and fear control and management. Honest Communication and managing strong feelings were required to develop and maintain productive, positive and healthy relation ships. Part 2 of the survey was titled Personal Leadership. It consisted of four skills that were essential to the learning and development of positive and responsible leadership. Personal Leadership was important because it required social skills, the ability to understand and respect the views of others, the ability to solve problems, and the ability to lead one's self in a positive way. Part 3 was titled Self Management in Life and Career. There were four emotional skills essential to the effective management of self. These skills consisted of Drive strength, Time Management, Commitment Ethic and Positive Personal Change. Self-Management required motivation and achievement drive, effective use of resources, personal commitment, and a positive approach to change. Part 4 was titled Intrapersonal Development. Two emotional skills were essential to self worth, confidence and personal competence. These emotional skills were self esteem and stress management. Intrapersonal Development required the full development of a strong personal belief system and the effective management of the pressures and stresses of life and work.

Inputs to NN based Student Success model (Emotional Indicators/Skills)

Interpersonal skills

Assertion: (AS)

Assertion is a key emotional skill essential for developing strong, positive and healthy relationships.

Leadership Skills

Comfort: (CO)

Comfort is a key emotional skill essential for developing and maintaining positive interactions with others in a social and /or leadership capacities.

Empathy: (EM)

Empathy is a key essential for honest and effective communication in social and/or leadership capacities.

Decision Making: (DM)

Decision-making is a key emotional skill essential for formulating and seeing choices in problem situations and for involving others in the solution to problems and conflicts.

Leadership: (LE)

Leadership is a key emotional skill essential for establishing and providing vision, momentum, and direction for others in ways that are valued and respected.

Self Management Skills

Drive Strength: (ST)

Drive strength is a key emotional skill essential for high performance, goal achievement and success.

Time Management: (MG)

Time Management is a key emotional skill essential to the effective management of self.

Commitment Ethic: (ET)

Commitment Ethic is a key emotional skill essential for success and satisfaction and is the inseparable companion of high achievement and personal excellence.

Intrapersonal Skills

Self Esteem: (ES)

Self Esteem is an emotional skill essential for learning about and developing self in all aspects of life.

Stress Management: (MA)

Stress Management is a key emotional skill essential to health, performance, and satisfaction in life and work.

Determinant of Student Success (outputs: problem areas for improvement)

Potential Problem Areas

Aggression: (AG)

Aggression involves the emotion of anger and needs to be understood and converted to the emotional skill of *Anger Control and Management*. Anger control and Management is a key emotional skill essential to the healthy and constructive expression of anger in relationship to self and others.

Deference: (DF)

Deference involves the emotion of fear and needs to be understood and converted to the emotional skill of *Fear Control and Management*. Fear control and management is a key emotional skill essential to the healthy and constructive expression of fear, worry, and anxiety in relationship to self and others.

Change Orientation: (OR)

Change orientation needs to be understood and converted to the emotional skill of *Positive Personal Change*. Positive personal change is a key emotional skill essential to healthy change and development throughout life.

Neural Networks

Neural Networks (NN) is massively parallel, distributed processing systems that can continuously improve their performance via dynamic learning. NN have more recently begun to emerge as an entirely new approach for the modeling of adaptive, distributed, and mostly nonlinear systems. NN are suited for applications involving complex systems. When applied correctly, a neural or adaptive system can outperform other methods[4]. Neural computers have opened the door to many applications that are difficult for conventional computers to carry out. An artificial NN model emulates a biological NN based on the human brain. The NN resembles the human brain in two ways. It acquires knowledge through learning. This knowledge is stored within inter-neuron connection strengths known as synaptic weights. The biological NN is composed of special cells called neurons that are partitioned into groups called networks. By way of comparison, the artificial NN is composed of Processing Elements, which contains the transfer function, and weights (which express relative strength of the input data or transfer data from layer to layer and to the output). The artificial NN can appear in many configurations called architectures. These architectures may have many different transfer functions, different number of Input Processing Elements (PE's), Output PE's, Hidden PE's and Hidden Layers. Key advantages of the NN are its ability of learning, recognition, generalization, classification and interpretation of incomplete and noisy inputs (data) and its ability to represent both linear and nonlinear relationships.

Training is the process of teaching the network what one wants it to learn. Neural networks are characterized by the pattern and strength of connections between the various network layers, the number of neurons in each layer, the dynamic learning algorithm, and the neuron activation functions. Generally speaking, a neural network is a set of connected input and output units in which each connection has a weight associated with it. During the learning phase, the network learns by adjusting the weights so as to be able to correctly predict or classify the output target of a given set of input samples. With supervised learning, the network is able to learn from the input and the error (the difference between the output and the desired response). Given the numerous types of neural network architectures that have been developed in the literature, three important types of neural networks often used for classification problems were implemented.

Multilayer Perceptrons (MLPs):
MLPs are layered feedforward networks typically trained with back propagation (learning algorithm). Their main advantage is that they are easy to use, and that they can approximate any input/output map. The key disadvantages are: they train slowly, and require a large amount of training data (typically three times more training samples than network weights) [5].

Generalized Feedforward Networks (GFN):
GFNs are a generalization of the MLP, which contains connections that can jump over one or more layers. In practice, generalized feedforward networks can often solve the problem much more efficiently [5].

Radial Basis Function (RBF):
RBF networks are nonlinear hybrid networks typically containing a single hidden layer of processing elements (PEs). This layer uses Gaussian transfer functions, rather than the standard sigmoid functions employed by MLPs. These networks tend to learn much faster than MLPs [5].

Simulation Results

The model used the above-mentioned 3 NN models and ten inputs in predicting problem areas inhibiting academic success. All three NN models were run under varied training cycles and number of hidden layers.

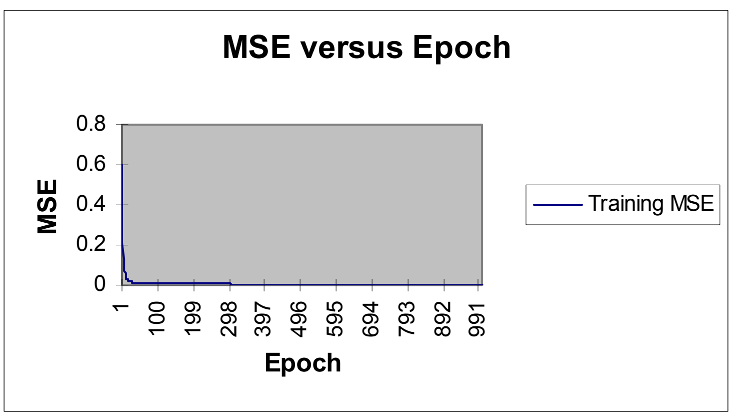

Figure 1: Training Results (MSE Vs. Training Cycles)

Ultimately, the GFN neural network with two hidden layers and a training cycle of 1000 epochs was chosen based on the quality of the output. The data below summarizes the attributes of the network model used. Figure 1 represents NN training. Figure 2 represents the ability of the neural model to predict the network output satisfactorily.

Training: Minimum Mean Square Error (MSE) = 0.0048
Final Mean Square Error (MSE) = 0.0048

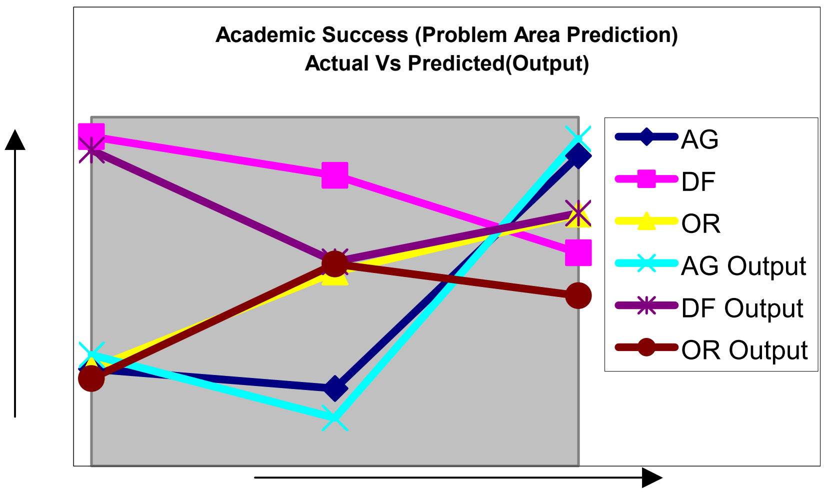

Figure 2: Testing Results

Table1: Sensitivity of EI Indicators

EI Indicators	AG	DF	OR
AS	0.169726908	0.384711742	0.053616002
CO	0.352551073	0.250111789	0.158556074
EM	0.015458676	0.155161232	0.015027603
DM	0.616325021	0.035952482	0.240603432
LE	0.169402629	0.04529383	0.029166793
ST	0.266284883	0.07975556	0.310405463
MG	0.014412257	0.065548152	0.138606176
ET	0.196476653	0.081372187	0.170795128
ES	0.159230709	0.030046551	0.180335626
MA	0.008211018	0.056893364	0.011032573

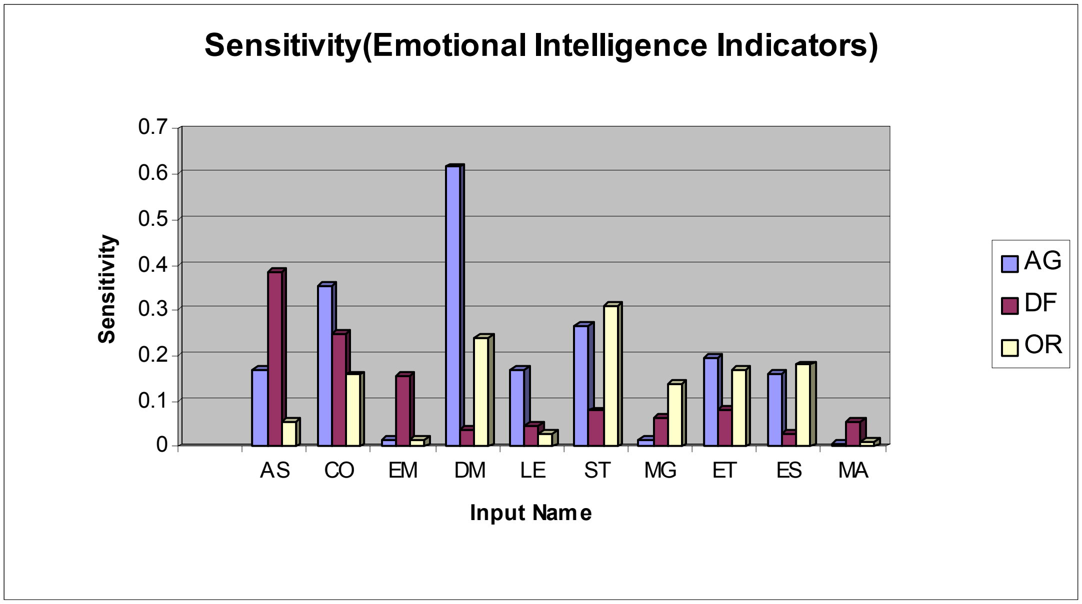

Figure 3: Sensitivity of EI indicators

Each Input is varied between its mean +/- a user-defined number of standard deviations while all other inputs are fixed at their respective means. Table 1 and Figure 3 represent the sensitivity of each Emotional Intelligence (EI) Indicators towards predicting the problems areas of Aggression (AG), Deference (DF) and Change Orientation (OR).

Conclusions and Future Work

It was observed that the neural network model selected performed well with satisfactory results. It easier to determine which of the inputs contributed significantly towards the required output by performing the sensitivity analysis on each input. Emotional skills contribute significantly towards the productivity and performance of students. Our research can serve as an excellent platform for the engineering students to track their present and future emotional skills profile, enabling them to enjoy life long learning and enhancing their quality of life, which in turn would foster academic growth and success.

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KENNETH NIX
Mr. Nix is an Alumni of Mechanical Engineering Department. He graduated in Fall 2004 with an undergraduate degree in Mechanical Engineering

GUADALUPE FERNANDEZ
Mr. Fernandez is an undergraduate student of senior standing in the Mechanical Engineering Department.

CHAD JURICA
Mr. Jurica is an Alumni of Mechanical Engineering Department. He graduated in Fall 2004 with an undergraduate degree in Mechanical Engineering

LAURA LOPEZ
Ms. Lopez is an undergraduate student of senior standing in the Mechanical Engineering Department.

RANJEET AGARWALA
Mr. Agarwala serves as a lecturer in the Mechanical Engineering department at Texas A&M University. His research interests are in the area of Adaptive Control, Neuro –fuzzy systems, Internet based Teleoperational systems and Robotics &Automation.

ROBERT A. MCLAUCHLAN
Dr. McLauchlan currently serves as Professor and Head of the Mechanical & Industrial Engineering Department at Texas A&M University-Kingsville. His research interests are in the area of Systems, Control & Signal Processing/Intelligent Control (Neural Networks, Fuzzy logic, Genetic Algorithms &Artificial Immune systems). Prof. McLauchlan is a registered engineer in the state of Texas.