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Predicting Mathematics Incompetence Effects on the Study of Digital Electronics Among Electrical and Electronic Engineering Students, using Artificial Neural Networks

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Abstract: Through proficiency effect analysis, the research aims to identify key engineering mathematics domains that are essential for students to succeed in Digital Electronics course. This investigation employs an artificial neural network (ANN)-based predictive model and focuses on Ghanaian Technical Universities as a case study. The study adopted the quantitative research design where random cluster sampling was used to select a total of 488 final year Higher National Diploma students from four technical universities in Ghana. The data consisted of mathematics achievement test scores and results of their Digital Electronics course. After testing a number of artificial neural network (ANN) architectures, the most accurate model was a multilayer perceptron neural network (MLPNN) with a 6-2-2 partition. The results showed, with high precision, that Functions and Algebra are two critical areas of mathematics that have the greatest impact on students' performance in Digital Electronics in electrical and electronic engineering studies.

Keywords: *Achievement, Activation Function, ANN, Cross-Entropy Error, Digital Electronics, Hidden Layers, Hyperbolic Tangent Function, Mathematics Failure, Multilayer Perceptron Neural Network.*

1. Introduction

In the fast-paced field of Electrical and Electronic Engineering, innovation and academic goals are greatly aided by the combination of mathematical proficiency and technological know-how. Upon starting the complex path of studying Digital Electronics, students come to a crossroads where mastery of mathematics becomes essential. This paper explores the fascinating field of predicting how mathematical incompetence may affect Electrical and Electronic Engineering students' study of Digital Electronics, in Ghanian Technical Universities. Using the capabilities of Artificial Neural Networks (ANNs), which emulates the human brain in solving a problem, we investigate how these sophisticated computational models can shed light on the complex relationship between success in grasping the concepts of five areas in the Higher National Diploma (HND) engineering mathematics courses' contents and the Digital Electronic course.

The branches of engineering mathematics that appear most useful in the study and application of digital electronics include Functions and Algebra (especially Boolean Algebra). The design and analysis of digital logic depend on these mathematical ideas [1]:

Algebra: Competence in Algebra is very important in all other branches of mathematics. In digital electronics, Boolean algebra is extensively used. [2] asserts that, 'Boolean algebra and synthesis of circuits were developed leading to new application in Digital Electronics'.

Functions: For digital electronics, it is essential to comprehend and manipulate functions. Mathematical functions are used to express logic functions such as combinational and sequential logic[3]. Analyzing the behavior and interactions within digital circuits is made easier with the study of functions.

Trigonometry and Complex Numbers: Even though they are not as immediately useful as functions and algebra, trigonometry and complex numbers can be useful in some digital electronics signal processing and analysis applications. For instance, signals may be represented by complex numbers in the context of Fourier analysis[4].

Calculus and Differential Equations: These topics seems to have less immediate bearing on the fundamental design and analysis of digital circuitry. They may, however, be useful in more complex subjects like signal processing, control systems, or specific subfields of digital electronics where dynamic behavior is taken into account[5].

Probability: The reliability of digital systems, error analysis, and the creation of error-detecting and error-correcting codes are all areas in which probability theory is pertinent. It becomes especially crucial in storage and communication systems [6].

There are a number of advantages of using ANNs rather than multiple regression models when predicting students' achievement in Digital Electronics based on their performance in specific engineering mathematics topics.

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Among these advantages are:

Non-linearity: Complex, non-linear interactions between input and output variables can be captured by ANNs. The correlations between various engineering mathematics domains and Digital Electronics performance may not always follow a linear pattern in educational datasets. Modelling such complex patterns by ANN usually produces more accurate results than linear models such as multiple regression, as the comparison study made by [7].

Feature Learning: The ANN can automatically pick pertinent characteristics from the engineering mathematics topics without requiring human feature selection[8]. ANN can reveal hidden patterns that conventional regression models might miss[9].

Generalization and flexibility of the model: ANNs can anticipate outcomes based on previously unknown data and adjust to new patterns[10]. This flexibility is helpful in educational environments where curricula and instructional strategies are subject to change.

This research is therefore an attempt to put up an adaptive system such as the ANN to predict the effect of incompetence in these areas of mathematics on the study of Digital Electronics among Electrical and Electronic Engineering Students, using ANN. The objectives of this study are therefore:

- To identify some suitable domains of mathematics that affect a student performance in Digital Electronics;
- To model an ANN that can be used to predict a student's performance in Digital Electronics course based on some predetermined data on some areas of mathematics for a student.

Though it is rarely used to analyze examination scores data, it should be noted that ANNs can be used to examine it more thoroughly than alternative approaches, such as regression analysis. There is strong evidence that ANNs perform analysis of accrued data more effectively than traditional techniques [11]. By delving into this relationship, we hope to improve our comprehension of the difficulties that students can encounter and, in the end, may inform on the teaching and learning methods in these areas of mathematics. Ultimately, the findings of this research try to empower educators and institutions in their commitment to enhancing the academic achievement and overall success of the Electrical and Electronic Engineering students.

This study specifically targets the complex relationships between five mathematics domains and students' performance in Digital Electronics. This is a departure from the few studies in the literature that employed more general environmental influences on the study of Digital Electronics[12] [13] [14] [15] [16]. Thus providing a basic analysis of the academic prerequisite for success in the Digital Electronics course, in which the ANN model may reveal hidden patterns [17].

2. Method

2.1. Research Design

The causal comparative design was used with the relational survey model. The relational survey model aims to measure the presence and degree of variation between two or more variables [18]. We aimed to describe the effects that students' drawbacks in mathematics have on their achievement in digital electronic course without any attempt to change or influence it.

2.2. Participants

The subjects of the study are the 2021/2022 final year HND electrical and electronic engineering students in the ten technical universities (TUs) in Ghana who have already completed their engineering mathematics courses over their first four semesters. These students form the population for this study. This population is made up of students who previously studied in Senior High Schools, and also those from the pure Technical Schools.

Four TUs were randomly selected from the ten. Second-year HND electrical and electronic students at Cape Coast Technical University (CCTU) who had just completed their fourth semester were selected for testing the MAT instrument. We anticipated that the data from the four technical universities will be homogeneous. This is as a result of a common entry requirement and syllabus for the HND electrical and electronic engineering program. Within the TUs that were randomly sampled, a cluster sample total of n = 488 students was obtained.

2.3. Research Instrument

De Lange's model of assessment is redesigned to measure students' mathematics incompetence in three dimensions: domain of knowledge (algebra, functions, trigonometry, calculus, and probability); levels of mathematics difficulty (low to high); and cognitive level (knowledge, comprehension, application, and HOT) [19]. The five mathematics content areas (domain of knowledge) were purposively selected from the HND electrical and electronic engineering curriculum in Ghanaian Technical Universities (TUs). The test items for the MAT were carefully planned to ensure that the level of difficulty is not above that of the content of the HND syllabus.

The Mathematics Achievement Test (MAT) used for this research were two types: the subjective type (MAT I) and objective type (MAT II). Both MAT I and MAT II were made up of five sections, A to E, covering the areas of Algebra, Functions, Trigonometry and Complex Numbers, Calculus and Differential Equations, and Probability, respectively. Both consisted of test items in each section that measured students' failure in getting the concepts in these areas of mathematics, as well as their cognitive failure according to the Bloom's taxonomy (that is, failure in knowledge, comprehension, applications, analysis, evaluation, and creativity) [20]. While MAT I consisted of five subjective test items that measured the aforementioned variables, MAT II consisted of twenty (20) objective test items in each section, making a total of 100 items, all within the scope of the engineering mathematics curriculum. Because of the volume of the test, MAT II was administered on three different occasions under standard examination conditions. The large number of items in the MAT II ensured repeated measurements in the cognitive domain and thus reducing the effect of using multiple choices in the measurements. We were also motivated by the positive impact multiple-choice question authoring and regular participation have on students' learning [21].

A secondary data consisting of each students' results in EEE207 (Digital Electronics) that was taken in the third semester of their studies in the universities were collected from the examination units of the four selected universities. These are the raw scores obtained from students' result broadsheets. Table 1 describes the variables used in this investigation.

Table 1. Variable description

Variable	Description
Independent Variables	
FALG	Students' failures score in Algebra in 20 objective test items and a surjective test, designed to cover all six levels of the Bloom's taxonomy. The total failure score was in percent.
FFUNC	Students' failure scores in Functions in 20 objective test items and a surjective test combined. The tests were designed to cover all six levels of the Bloom's taxonomy. The total failure score was in percent.
FTRIG	Students' failure scores in Trigonometry and Complex Numbers in 20 objective test items and a surjective test combined. The tests were designed to cover all six levels of the Bloom's taxonomy. The total failure score was in percent.
FCALC	Students' failure scores in Calculus and Differential Equations in 20 objective test items and a surjective test combined. The tests were designed to cover all six levels of the Bloom's taxonomy. The total failure score was in percent.
FPROB	Students' failure scores in Probability in 20 objective test items and a surjective test combined. The tests were designed to cover all six levels of the Bloom's taxonomy. The total failure score was in percent.
Dependent Variable	
CATEE207	Categorized students' performance in EEE207 (Digital Electronics), a Higher National Diploma (HND) Course, taken in the third semester of their program. The categories were, 0=low performance; 1=average performance; 2=high performance,

2.4. Data Analysis

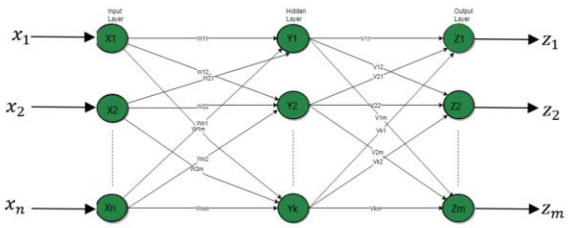
The IBM SPSS version 28 was employed in the investigation. This makes use of the multilayer perceptron neural network (MLPNN), which minimizes default prediction errors. An input layer, a hidden layer with radially symmetric functions and unsupervised learning for hidden neurons were all part of the neural network architecture. Moreover, there existed an output layer featuring a categorical node that helped in conducting weighted sum calculations based on outputs from the hidden layer, along with performing index class computation for input patterns[22][23].

For training, testing, and holdout, the model was constructed using different nodes in one or two hidden layers, with varying dataset partition rates: ANN1 (50%-30%-20%), ANN2 (60%-20%-20%), and ANN3 (70%-20%-10%). Neural networks establish models by learning correlations between independent and dependent variables, justifying outcomes by linking predicted and actual values. This makes it possible for ANNs to clarify how cause and effect criteria relate to one another [24]. Neural network technologies outperform classical computing systems in these kinds of applications, where problems are solved by following a set of instructions[25].

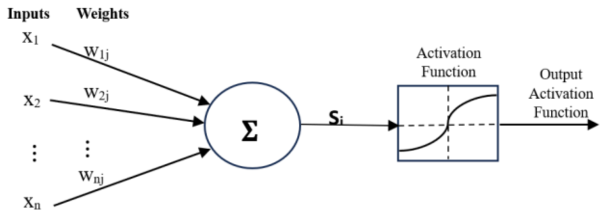
2.5. The ANN Approach

ANNs are often used computational methods that enable the simulation of animal brain operations, which helps solve multifaceted problems[26]. Artificial neurons are used as information processing units in perceptron-type neural networks (PTNNs), which are arranged in layers and coupled by synaptic weights. By using this method, neurons can transmit and filter information as needed, which makes it possible to build analytical models that classify data that has been stored according to the network's information processing rules[24]..

ANNs usually have three layers: input, hidden, and output. Depending on the needs of the research, hidden layers can be added to three-layer models in between the input and output levels. While neurons in the same layer are not connected, each neuron has the ability to connect with neurons in the layer below it, allowing for the processing of information in interconnected artificial neurons.



(a)



(b)

Fig 1. Artificial Neural System Architecture: Sj - sum of the weighted input

Figure 1 illustrates the architecture of the artificial neural system. In Figure 1a, the input layer gathers statistics about variables from the provided dataset, and subsequently, the hidden layer performs the data processing. The layer used to forecast continuous metrics and create the categorical class label is known as the output layer. The input layer values that are sent to the inner hidden node are multiplied by weights, which are a predefined set of values.

Subsequently, the measurements are summed to generate a singular value, which serves as an input to a nonlinear mathematical function referred to in artificial neural networks as the activation function. A numerical number in the range of 0 to 1 is the output of the nonlinear activation function. In Figure 1b, the total sum of the weighted input values entering node j, along with the output activation function, which transforms the weighted input of the neurons into its output activation (commonly using the sigmoid function), can be expressed through the following equations:

$$S_j = \sum_{i=1}^{n} x_i \omega_{ij} \quad (1)$$

$$O_j = \frac{1}{1+e^{S_j}}. \quad (2)$$

The ANNs' neurons operate through two distinct stages: the training stage and the usage stage [27]. During the training stage, real input and output datasets are used as examples to train the system to anticipate outputs. The error function uses the variance between the target output measures and the obtained measures to control learning, which starts with random weights and is adjusted to fit the given situation by using gradient origin examination algorithms like back-propagation[28].

Furthermore, the weights are where the error function belongs, and they need to be improved if the error is to be reduced. The k designated training pairs of dataset, $\{(x_1, t_1), (x_2, t_2), \ldots, (x_k, t_k)\}$, of n inputs and m dimension routes, may be explained by n inputs and m outputs. Equation (3) can be used to determine the error for each output neuron:

$$E_j = \frac{1}{2}(O_j - t_j)^2. \quad (3)$$

Equation (4) also shows how to minimize the error in the network function:

$$E_j = \frac{1}{2}\sum_{j=1}^{k}(O_j - t_j)^2 \quad (4)$$

where O_j donates the output that the network produces after processing the input pattern x_i from the training dataset. t_j is the target measurement. Every weight is adjusted by adding a specific amount to its initial value during the training phase, using the update rule for adjusting the weights:

$$\Delta\omega_{ij} = -\gamma \frac{\sigma E}{\sigma \omega_{ij}}, \quad (5)$$

where $\Delta\omega_{ij}$ represents the change in weight for the connection between neuron i and neuron j; γ is the learning rate, a hyperparameter that determines the size of the steps taken during the weight updates. It controls how much the weights are adjusted during each iteration of the training process; σE represents the sensitivity of the error to changes in the weighted sum; and $\sigma\omega_{ij}$, the partial derivative of the weighted sum of inputs to neuron j with respect to the weight ω_{ij}, represents how much the weighted sum changes when the weight is adjusted.

2.6. The Multilayer Perceptron Approach

The above-discussed perceptron-based approach has a limitation; it is usually only suitable for data that is linearly identifiable. The perceptron-based model is expanded to a more complex design known as the multilayer perceptron (MLP) when working with non-linear datasets [29]. Moreover, MLP may be thought of as a neural network made up of interconnected neuronal layers, in which neurons in a layer can only use their output as an input when they are in a layer above it (see Figure 1). And, when these neurons undergo non-linear activation functions, such as the sigmoid function[30], then, the high non-linearity of the dataset can be encompassed by the MLP neural network, demonstrating that complex-enough MLPs may be applied to approximate any continuous function at a random error[31].

The weight associated with the connection from the *i*th neuron in the *l*th layer to the *j*th neuron in the (*l* + 1)th layer, denoted as (*l* + 1)*j*, serves as a means to validate the *i*th neuron in the *l*th layer. This can be expressed through the equation:

$$y_{li} = f_{li}(z_{li}); \;\; z_{li} = \sum_{j=1}^{n_l-1} \omega(l-1)_j, \;\; li\,\gamma(l-1)_j + b_{li}, \quad (6)$$

where y_{li} is the output, f_{li}, the activation function, b_{li} the bias and n_l is the number of neurons for the *l*th layer. In simple terms, the total of the weighted outputs from the neurons in the lower layer activates a single neuron. Further, it is often possible to utilize the following objective function for the binary classification, which is aimed to be minimized:

$$E(\theta) = \frac{1}{n}\sum_{(x,y)\in D}(y-\hat{y})^2, \quad (7)$$

where D represents a set of training data, the predicted output $\hat{y}$ is obtained through the MLP using the given input *x* and a set of weights and biases denoted by θ. The gradient descent method is used to minimize the objective function $E(\theta)$, adjusting parameters in proportion to their present gradient[32]. After training, network weights are established and used to compute output measures for initial input samples[24]. The feedforward algorithm enables us to rapid complete the MLP prediction [33].

2.7. The Number of Necessary Hidden Units

An MLP needs to calculate the necessary number of hidden units (NHUs) in order to reach a certain approximation order. The NHUs also affect the number of independent values that need to be modified in order to change the network parameters, as well as the success of the given approximation instruction for the randomly adequate smooth function[34]. Moreover, it is not so simple to compute several MLP parameters. Also, there is more than one NHU defined for the network parameters. Furthermore, there is more than one NHU defined for the network parameters. This scenario can be explained if the hidden units are dispersed in several hidden levels in a variety of ways. Finding the essential NHUs is the goal in the interim, and when the number of hidden units is known, it is crucial to define the maximum amount of the parameters [35].

With $n_0 \in \mathbb{N}$ inputs and a smooth activation function, a multilayer perceptron neural network with one hidden layer can only implement an approximation order $N \in \mathbb{N}$ for all functions $f \in C^N\ (K \to \mathbb{R})$. The main finding indicates no necessity for limiting hidden layers, though no more than two are typically required. A single hidden layer is sufficient in most cases, yet certain situations may demand distributing hidden units across two layers to meet network constraints [36]. This can be described using the resulting Equation (8).

$$\binom{N+n_0}{n_0} \le (n_0+2)(n_0) + 1 + 2\sqrt{n_0}, \quad (8)$$

The presence of *n* hidden units, as defined in Equation (11), plays a crucial role in achieving the desired approximation order $N \in \mathbb{N}$ for all functions $f \in C^N\ (K \to \mathbb{R})$.

$$n \ge \binom{N+n_0}{n_0} \quad (9)$$

Alternatively, the computation of the required number of hidden units to attain a specified approximation order may be done by the use of Equation (10):

$$n \ge 2\sqrt{\binom{N+n_0}{n_0} + 2(n_0+1)} - n_0 - 3 \quad (10)$$

The needed parameter count can be attained with a single hidden layer in a multilayer perceptron neural network. Equations (12) and (13) below, however, can be used to derive the required number of parameters for the MLP neural networks when using two hidden layers.

$$n_1 = \left\lceil \frac{n+n_0-1}{2} \right\rceil, \quad (11)$$

$$n_2 = n - n_1 = \left\lceil \frac{n-n_0+1}{2} \right\rceil, \quad (12)$$

If the number of inputs is known, Equations (10)–(12) may be useful for determining the number of the required hidden units and its variation to hidden layers[37].

3. Research Results

Using IBM SPSS version 28, neural network models were constructed and their precision was assessed. The subsequent subsection details the outcomes of the research, based on the development, training, and testing phases of the ANN models.

3.1. The Preliminary Analysis

Five independent variables, providing the failure levels in the various mathematics domains (topics) in the test, were analyzed and Table 1 shows the descriptive statistics. That is, the means, standard deviations, skewness and kurtosis for the MAT failure scores.

Table 1. Descriptive statistics for MAT failure scores

						Skewness		Kurtosis	
Variable	N	Min	Max	Mean	Std. Dev	Statistic	Std. Error	Statistic	Std. Error
FALG	488	10	95	44.13	13.602	-0.042	0.111	0.292	0.221
FFUNC	488	5	80	41.86	12.045	-0.047	0.111	0.197	0.221

FTRIG	488	5	95	41.64	11.163	0.229	0.111	1.378	0.221
FCALC	488	15	90	44.87	11.874	0.567	0.111	0.750	0.221
FPROB	488	15	100	54.66	13.463	0.118	0.111	0.528	0.221
Valid N	488								

SPSS output

The values of the skewness and kurtoses shown for the data in Table 1 indicates that the distribution of the failure marks, scored by the 488 students is approximately normal. Again, from Table 1, students were found to perform poorest in probability (FPROB: mean=54.66, Std Dev=13.463). It may interest you to note that probability was the only area in the MAT which students scored the maximum failure mark (max = 100). The second poorest area mathematics area was calculus and differential equations (FCALC: mean=44.87, Std Dev=11.874). algebra also followed as the third area of difficulty (FALG: mean=43.13, Std Dev=13.602), whereas trigonometry and complex numbers was the most well-handled area in the MAT (FTRIG: mean=41.64, Std Dev=11.163).

In addition, the Pearson's correlation coefficients used to assess the relationships among the variables, including the dependent variable (EEE207) are presented in Table 2. This helped in identifying the significant correlations between achievements in EEE207 and the MAT failure score variables at the 0.01 two-tailed kevel of significance.

Table 2. Relationships between research variables

	FALG	FFUNC	FTRIG	FCALC	FPROB	EEE207
FALG	1.000					
FFUNC	0.675^{**}	1.000				
FTRIG	0.603^{**}	0.626^{**}	1.000			
FCALC	0.517^{**}	0.481^{**}	0.613^{**}	1.000		
FPROB	0.582^{**}	0.572^{**}	0.542^{**}	0.549^{**}	1.000	
EEE207	-0.432^{**}	-0.431^{**}	-0.395^{**}	-0.311^{**}	-0.389^{**}	1.000

Notes: **p<0.01 (Pearson's correlation, two-tailed hypothesis test used).

Marching the MAT failure scores to the achievement in EEE207, it can be seen that the highest significant negative correlation was between EEE207 variable and FALG (r = -0.432, p < 0.01), while the next highest significant negative correlation with FFUNC scores was shown with EEE207 variable (r = -0.147, p < 0.01). FCALC showed the lowest significant negative correlation with EEE207. The significant negative correlation between the EEE207 and each of the other variables indicates that not understanding the concepts of Algebra, Functions, Trigonometry and Complex Numbers, Calculus and Differential Equations, and Probability would each have a negative effect on the achievement in Digital Electronic in Electrical and Electronic Engineering Education.

3.2. Description of Parameters for Neural Network Training and Testing

It is important critical to establish an ideal structure with enough neurons and hidden layers. Over-fitting can result from having too many neurons, whereas too few might lead to insufficient data processing[38]. Keeping this in mind, MLP neural networks were selected for analysis of the data. They underwent training by the use of the backpropagation learning algorithm, and the weight updates were performed by the use of the gradient descent method to minimize the error function gradually. Different partition rates of the dataset were randomly given for training, testing, and holdout: ANN1 = 50%–30%–20%, ANN2 = 60%–20%–20%, and ANN3 = 70%–20%–10%.

Prior to the training process, standardization of all the covariates was performed. The scaled conjugate gradient algorithm was used to determine the model construction, taking into account a number of parameters such as initial sigma, initial lambda, interval center, and interval offset. Furthermore, the parameters of the interval center, denoted as a_0 and a, compelled the simulated annealing algorithm to produce random weights within the range of $a_0 - a$ and $a_0 + a$, thereby consistently minimizing the error function through successive iterations. Additionally, 0.0000005 was set as the initial lambda and 0.00005 as the initial sigma. Also, the interval offset was set to 0.5 and the interval center was defined as zero. Section 3.3 below provides a summary of the basic MLP configurations.

3.3. Results of Case Processing

Table 4. Network information for case processing

Layer Description				
Layer	**Partitions**	***Number of Units**	**Activation Function**	**Variable Description**
ANN1:5-3-2				
Input	47.9%(232)	78	-	FPROB, FCALC, FTRIG, FFUNC, FALG
Hidden	32.4%(157)	2	Hyperbolic tangent	
Output	19.6%(95)	3	Softmax	Dependent variable CATEE2027: 0=low performance, 1=average performance, 2=high performance
ANN2:6-2-2				
Input	62.3%(302)	78	-	FPROB, FCALC, FTRIG, FFUNC, FALG
Hidden	18.8(91)	3	Hyperbolic tangent	
Output	19%(92)	3	Softmax	Dependent variable CATEE2027: 0=low performance, 1=average performance, 2=high performance
ANN3:7-2-1				
Input	67.9%(330)	80	-	FPROB, FCALC, FTRIG, FFUNC, FALG
Hidden	21.4%(104)	3	Hyperbolic tangent	
Output	10.7%(52)	3	Softmax	Dependent variable CATEE2027: 0=low performance, 1=average performance, 2=high performance

Notes: N= number of cases divided for calculations. Standardized rescaling method for covariates; Error Function = cross-entropy. *excluding the bias units.

The study investigated whether or not, the MLP neural network can recognize the areas (topics) of mathematics among the five selected ones that impact students' achievement in the Digital Electronics course (EEE207). Table 4 displays the neuron count in each layer of each of the three models, and 5 independent variables: FALG, FFUNC, FTRIG, FCALC and FPROB. Three nodes were used for the hidden layer computation in the automatically generated MLP neural network, and an additional three nodes were used for the output layer, which described the outcomes of the dependent variable, EEE207, by categories (CATEE207). To each layer, different functions were applied: the output layer employed the softmax function, while the hidden layer used the activation function as the hyperbolic tangent. Moreover, when employing the softmax function, the validation of the model was done using cross-entropy as the error function.

The IBM SPSS version 28 program was used to predict HND students' performance in the Digital Electronic course (EEE207): 1 = low performance, 2 = average performance, and 3 = high performance) using the 5 variables described in Table 1. The optimum ANN network had 78 input nodes, 3 hidden nodes, and 3 output nodes in the achievement of EEE207 as was measured according to the three categories (CATEE207). Table 5 presents the summary of the training, testing and holdout sample results for the models constructed.

Table 5. Summary for the designed models

	Layer Description	**ANN1**	**ANN2**	**ANN3**
1Training	Cross entropy error	41.256%	28.577	48.675
	Percent incorrect predictions	17.5%	14.7%	18.2%
	Training time	0:00:00.06	0:00:00.16	0:00:00.19
Testing	Cross entropy error	25.617	14.215	12.391

	Percent incorrect predictions	19.7%	20.9%	14.4%
Holdout	Percent incorrect predictions	26.3%	15.2%	25.0%

[1]Notes: Stopping rule used = consecutive step(s) with no decrease in error. Dependent variable: Achievement in Electrical and Electronic Engineering Education (AEEE): 0 = low performance, 1 =average performance, and 2 = high performance. Error computations are based on the testing sample.

The ANN2 model was found as having the lowest value of cross-entropy error, which was recorded at 28.577, indicating the ability of the model to predict the level of knowledge in EEE207. The study's findings show that, for the training and testing samples, the ANN2 model's percentages of incorrect predictions were 14.7% and 20.9%, respectively, whereas the holdout dataset has a degree of inaccurate predictions of 15.2%. The training process was carried out till the error function decreased in one successive step. Table 6 provides the confusion matrix, or ANN2 model case classification, for CATEE207 as categorical dependent variable, broken down by partition. The ANN2 model's projected result for each scenario was deemed accurate if the predicted probability exceeded 0.5[39]. Table 6 shows that 258 out of the 302 cases of the EEE207 measured by the three categories in the training dataset and 72 out of 91 variables in the testing sample were accurately identified by the ANN2 network. Overall, 85.3% of the training set's cases and 79.1% of the testing set's cases were correctly identified by model ANN2.

Within the holdout sample, the predicted low performance rate, average performance rate, and high-performance rates were computed as 36.4% 36.4%, 100% and 0% respectively, with 84.8% accuracy of the model. These percentages presented distinct probabilities for the predictions corresponding to the three categories of the dependent variable, CATEE207. After further processing, the ANN2 model was assessed using the ROC curve, which showed the classification performance for all possible cutoffs by a sensitivity vs. specificity diagram.

Table 6. Survey sample classification of the ANN2 model

Sample	**Observed**	**[1]Predicted CATEE207**			
		Low Performance	**Average Performance**	**High Performance**	**Percent Correct**
Training	Low performance	7	27	0	20.0%
	Average performance	5	242	0	98.0%
	High performance	0	21	0	0.0%
	Overall percent	4.0%	96.0%	0.0%	85.3%
Testing	Low performance	1	12	0	7.7%
	Average performance	2	71	0	97.3%
	High performance	0	5	0	0.0%
	Overall percent	3.3%	96.7%	0.0%	79.1%
Holdout	Low performance	4	7	0	36.4%
	Average performance	0	74	0	100.0%
	High performance	0	7	0	0.0%
	Overall percent	4.3%	95.7%	0.0%	84.8%

1Notes: Dependent variable: CATEE207

Table 7 displayed the area under the curve (AUC) for models' sensitivity and specificity metrics for AN1, AN2 and ANN3. This AUC reflects the complete representation of the ROC curve concerning the three performance categories (CATEE207) of the EEE207 variable: low performance, average performance, and high performance.

Table 7. Area under the ROC curve

		ANN1	ANN2	ANN3
		50%-30%-10%	**60%-20%-20%**	**70%-20%-10%**
		Area	**Area**	**Area**
CATEE207	0=low performance	0.744	0.807	0.790
	1=average performance	0.634	0.676	0.716
	2=high performance	0.462	0.537	0.636

The ANN models established based on CATEE207 had their ROC curve placements summarized with the help of the areas under the curves, which were used as dimensional indices. This information is very important for our discussion as it offers a meaningful explanation for academics[40]. The AUC displayed in Table 7 represents the probability that a randomly selected student can be effectively assessed or ranked upon enrollment in the EEE207 course. From Table 7, the highest AUC value of 0.807 (ANN2, CATEE207 group 0) indicates that the performance in Digital Electronics (EEE207) course demonstrated strong predictive ability in classifying students who had enrolled in the HND electrical and electronic engineering program and taken the EEE207 course. Figure 2 illustrates a graph of sensitivity and specificity, constructed based on both training and testing illustration. In Figure 2, the outcomes of the ROC curve for the ANN2 model are illustrated, using research data divided for analysis as follows: 60% for training, 20% for testing, and another 20% for holdout. It should be noted that, the more precise the classification, the further the curve deviates from the 45-degree reference line. After measuring the area under the curve, the low performance category showed the best result, 0.807 (compared to 0.676 for the average performance category and 0.537 for the high-performance category).

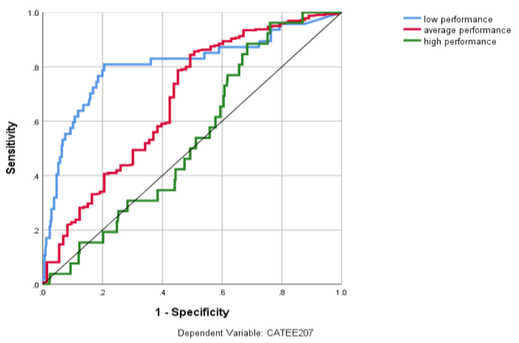


Figure 2. ROC curve for the ANN2 model

Moreover, Figure 3 displays cumulative gains, representing the correct classifications made by the ANN model compared to chance outcomes, that is classifications without the use of the model.

The gain chart in Figure 3a demonstrates the performance of the ANN2 model. Specifically, in the low-performance category, as indicated by the point (10%, 45%) on the curve, if the network evaluates these data and organizes all scores based on the predicted pseudo-probability of low performance, the top 22% is anticipated to encompass roughly 100% of all cases falling into the low-performance category. Furthermore, it is not necessary to choose all the scores in order to locate all the identified low performing students in the dataset. This indicates that the efficiency of the classification determined by the ANN model is shown on the gain chart. By assessing the baseline and curve positioning, we can gauge the extent of the gain. It can be inferred from this rule and Figure 3a that the developed model exhibits a notably higher overall gain, signifying commendable performance in the low-performance group. However, it is evident that the predictions for both the average and high-performance groups are not precisely accurate.

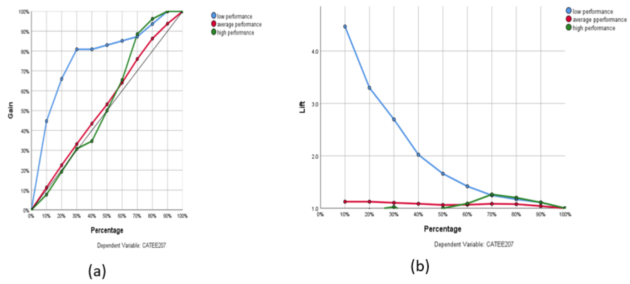


Figure 3. Model performance measurement: (a) Cumulative gains; (b) Lift chart by the ANN2 model.

The gain or lift diagrams only assess performance of the model in a subset of the population, in contrast to the confusion matrix, which estimates models on the entire population. The lift factor, which measures the effectiveness of a predictive model compared to random chance, was calculated using the measurements derived from the gains chart. According to [41],when the lift factor is greater than 1, it means that the model is performing better than random chance, and when it is less than 1, it means the opposite. For the low performance group in figure 3a, the lift at 45% was determined as 45%/10% = 4.5, as plotted in Figure 3b. The value therefore shows that ANN2 is more efficient in prediction than random chance.

Table 8 highlights the significance of evaluating independent variables in the neural network models that were designed. It displays the relative and normalized importance of each independent variable's impact found in the ANN1, ANN2, and ANN3 models. The values in Table 8 revealed that FUNC exhibited the highest importance among all predictors, with a normalized importance of 100%. Notably, this maximum normalized importance for FUNC was observed exclusively in the ANN2 model.

Table 8. Independent variable importance

Variable	ANN1 50%-30%-20%		ANN2 60%-20%-20%		ANN3 70%-20%-10%	
	Importance	Normalized Importance(%)	Importance	Normalized Importance(%)	Importance	Normalized Importance(%)
FPROB	0.192	80.8	0.219	97.7	0.236	100.0
FCALC	0.217	91.1	0.149	66.6	0.199	84.6
FTRIG	0.188	79.1	0.184	82.1	0.203	86.4
FFUNC	0.238	100.0	0.224	100.0	0.176	74.5
FALG	0.165	69.3	0.223	99.2	0.186	79.1

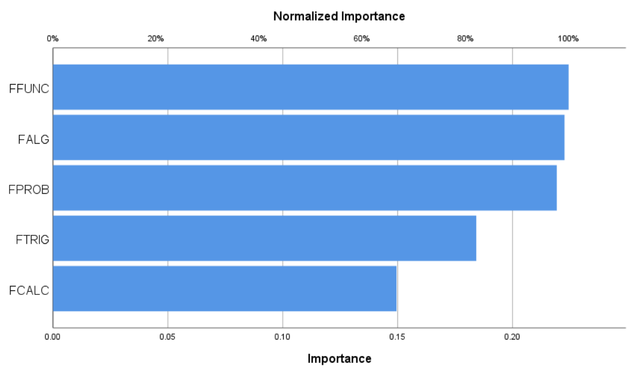


Fig 4. Normalized importance by the ANN2 model

For a clearer picture of the significance of the areas (topics) of mathematics in students' achievements in Digital Electronics, the charts of normalized importance for ANN1, ANN2, and ANN3 models were also provided. Figure 4 shows the chart for ANN2 which has been so far found to be optimal. When analyzing the results in Table 8 and Figure 6, it should be noted that all the independent variables were important predictors of students' achievement in Electronics, since they all have normalized importance of greater than 0.5. In the ANN2 model, FFUNC exhibited the highest importance (100%), followed by FALG (99.2%), FPROB (97.7%), and FTRIG (82.1%). CALC had the lowest importance (66.6%) among the predictors analyzed.

4. Discussions

Assuming nonlinearity in students' academic achievement helps answer the complex question of which of the areas of mathematics would have the most negative impact on the Digital Electronic course, if its concept is misunderstood. In other words, the most important in the situations where a number of topics are taught together for the benefit of understanding the Digital Electronic course in the tertiary institutions.

An MLPNN was trained by the back-propagation algorithm to yield the mathematics areas that negatively affect the achievement in Digital Electronics if its concept is not properly grasped. Though influence of mathematics on electrical and electronic engineering education, and engineering education as a whole, has been widely explored in the scientific literature, this study sought to predict which mathematics topic would have the greatest negative impact on Digital Electronic course among the Higher National Diploma students in the Technical Universities in Ghana, when its concepts are understood. In other words, the most important among the mathematics areas: Algebra, Functions, Trigonometry and Complex Numbers, Calculus and Differential Equations, and Probability to the Electrical and Electronic Engineering students who take the Digital Electronics course, was investigated in this study. This study deemed very important, especially in this technologically advancing world where professionals in the field of digital electronic need to be abreast with the changing technology. These students may need to be trained in this critical mathematics areas in order to comprehend properly the concepts of the digital electronics. Again, students on the electrical and electronic engineering training programme may identify the need to concentrate on the mathematics area which is critical to the digital electronic course.

In this study, we found that, there are significant negative correlations between students' failure scores in all the five areas of mathematics and the Digital Electronics courses (see Table 2). Our further analysis by the ANN showed that, though all the mathematics areas of study are important, the most two critical areas of mathematics in whose failure negatively affect students' achievements in Digital Electronics course are Functions and Algebra. Given the inverse relationship between the achievement in Digital Electronics course, and these two factors, we can predict that managing the teaching and learning of Algebra and Functions well in engineering mathematics in electrical and electronic engineering education could prevent students' low achievements in the Digital Electronic course.

To identify the ideal number of neurons, hidden layers, and transfer functions for predicting crucial mathematical areas influencing student success in the digital electronics course, a number of ANN models with MLP structure were developed and assessed. These findings are consistent with those of earlier studies[42][24]**.**

The results in Table 5 indicate that MLPNN (ANN2) is the best model. This model used 6–2–2 architecture, featuring 78 input neurons, 3 hidden neurons, and 3 output factors. The outcomes from the model employing a hyperbolic tangent threshold function demonstrated the lowest cross-entropy error rates, registering at 28.577 during training and 14.215 during testing. Superior validation results were shown by the ANN2 model, which used a 60%-20%-20% split for training, testing, and holdout data, respectively. The hidden layer of the model used hyperbolic tangent activation, and the output layer used softmax. It accurately predicted academic performance in Digital Electronics for all levels of students.

It was essential to design a neural network structure with the right hidden layers and neurons in order to precisely pinpoint the elements that improve students' understanding of digital electronics. Furthermore, network accuracy was evaluated using lift charts and ROC curve cumulative gains, which provided the optimal combination of sensitivity and specificity as in [40].

The importance of independent variables in the ANN2 model suggests that low performance in Digital Electronics is largely attributed to students' difficulty in understanding the concepts of three specific mathematics topics: Functions (FFUNC, normalized importance = 100%), Algebra (FALG, normalized importance = 99.2%), and Probability (FPROB, normalized importance = 97.7%). As exposed by [43], that ability in Digital Electronics depends on ability in mathematics, and Functions, Algebra and Probability appear to be more pronounced in their importance [44].

Some unexpected outcomes were noted in the ANN2 classification model. Mathematics in general is known to be an important predictor of electrical and electronic engineering students' performance[45]. It essentially activates students' higher-order thinking abilities[46]. One would have however readily expected failure in Calculus and Differential Equations to have had the most negative impact on ability in Digital Electronics[47]. Functions emerged as the most important factor for predicting students' performance in Digital Electronics (FFUNC, normalized importance = 100%), followed by Algebra (FALG, normalized importance = 99.2%), and then Probability (FPROB, normalized importance = 97.7%) and Trigonometry (FTRIG normalized importance = 82.1%). These were all seen as very strong predictors of students' performance in Digital Electronics. In the context of the performance of the students, Calculus and Differential Equations emerged as moderate predictor of students' performance in Digital Electronics (FCALC normalized importance=66.6%). These results confirm the literature that suggests that, although many fields of mathematics have applications in many engineering domains, a solid background in Algebra, including Boolean algebra and Functions are particularly crucial for digital electronics[1]. The reliability of digital systems, error analysis, and the creation of error-detecting and error-correcting codes are known to be crucial in Digital Electronics studies and practice[48]. These are all areas in which probability theory is pertinent, and the findings show its importance in predicting the performance of the students. It becomes especially crucial in storage and communication systems [6]. Critical examination of the results of this study confirms the wide applications of Algebra and Functions in the other three domains of mathematics whose importance to the study of digital electronics were also studied. In other words, one needs the to understand the basic concepts of Algebra and Functions in order to apply Trigonometry and Complex Numbers, Calculus and Differential Equations, and Probability to the study of Digital Electronics[49]. This gives meaning to the great importance of Functions and Algebra in prediction of students' performance in Digital Electronics course, as revealed in this study.

It should be noted that, the ANN2 model, using an MLPNN, accurately predicted average performance in Digital Electronics based on 78 criteria. Validation tests yielded 97.3% probability, but accuracy for low and high performance was notably low. The ANN2 model is still important for predicting all the three categories of students' performance because the completion of the engineering mathematics courses, with appropriate methods of teaching and learning is expected to reduce students' incompetence in the five selected mathematics domain and thereby increase their performance in Digital Electronics course. The opposite would decrease their performance in Digital Electronics.

Although this study provided accurate prediction of students' performance, there were some limitations. First, data from a single year group of study were used in the study. Although a reasonable number of units were sampled from institutions with well-positioned geographical locations[50]. Academic year group-based study may have problems with variations in the common methodology. The study employed three forms of the data iteration and a thorough data analysis to get over this limitation[24]**.** The use of the De-Lange's assessment model was also used to ensure adequate fairness in measuring students' incompetence in Algebra, Functions, Trigonometry and Complex Numbers, Calculus and Differential Equations, and Probability[19]. However, for future research, we suggest using a combination of academic year cohort groups for measuring mathematics competence or incompetence, and predictions of performance in Digital Electronic course.

This study also has a practical implication. For the curriculum developers, the results of this study are essential for setting pre-requisites for registering and studying the Digital Electronics course. Our findings point out that electrical and electronics engineering students who want to do well in the Digital Electronics course need to put in great effort to first, understand the concepts of all these five engineering mathematics areas, especially Functions, Algebra and Probability. To the instructors in the electrical and electronic engineering programme, efforts to shifts their levels of performance in the Digital Electronics course from low and average to high, is crucial for the challenges and practices in the 21st century[51]. The enquiry based method as investigated by a number of researchers including [52] may be a recommended mode of delivery in both the engineering mathematics and Digital Electronics courses.

5. Conclusion

The back-propagation technique was used to train a multilayer perceptron neural network, which identified some key mathematical topics that, if their concepts are not fully understood, significantly contribute to low performance in the study of digital electronics. The multilayer perceptron neural network was trained using the back-propagation approach. The results indicate that the MLPNN achieved the maximum accuracy when it used a 6-2-2 partition, standardized rescaling for covariates, and a hyperbolic tangent activation function with 3 units in a single hidden layer in conjunction with the back-propagation algorithm, which revealed some important insights.

The optimal ANN model was determined based on the lowest value of the cross-entropy (28.577), an accuracy rate of 97.3%, and the area under the ROC for each category using the predicted pseudo-probability (0.807 for low performance, 0.676 for average performance, and 0.537 for high performance). Furthermore, the MLPNN emerges as the optimal ANN2 model for predicting the three performance categories. However, when considering individual estimations, the choice of activation function and the configuration of hidden layers or neurons becomes highly specific to each case.

Furthermore, the neural network analysis revealed that, the most powerful predictors of students' achievement in Digital Electronics among the areas of mathematics chosen for our study are Functions (FFUNC, normalized importance = 100%), Algebra (FALG, normalized importance = 99.2%), and Probability (FPROB, normalized importance = 97.7%).

Future research on complex networks in education, such as influences of various domains of mathematics knowledge on achievements in engineering studies, may place greater emphasis on indicators or comprehensive methodologies that more accurately capture the ways in which these cognitive processes produce responses. While there is convincing evidence that the suggested neural network model can be efficiently applied in predicting students' achievement levels in Digital Electronics, aiding instructors in designing lessons to avert failure or low performance, it is essential for future studies to validate these findings using samples from diverse tertiary institutions.

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