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Machine Learning Model Based Analysis of Test Anxiety's Effects on Academic Achievement

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Abstract

Recent advancements in artificial intelligence (AI) and machine learning (ML) have significantly transformed healthcare education by enhancing efficiency, accuracy, and standardization in patient data analysis, while also being applied to explore the impacts of test anxiety and self-efficacy on academic achievement. A study using a feedforward artificial neural network, specifically Multi-Layer Perceptrons (MLPs), identified four critical factors for academic success: having a positive mindset (AR1, importance rate 0.997), monitoring and evaluating achievements (AR5, 0.996), a well-thought-out plan (AR2, 0.981), accountability for progress (AR3), and acknowledging stress and negative emotions (AR4). Additionally, the study highlighted key test anxiety factors, such as visible signs of nervousness before a test (AT1, 0.146) and heightened nervousness during exams (AT7, 0.126), which impact academic performance. Using machine learning, distinct patterns in academic achievement and test anxiety were identified across student groups, forming a "blueprint" for targeted interventions to improve academic outcomes. A predictive model was also developed to

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forecast data and analyze future conditions, enabling educators to proactively address challenges related to test anxiety, self-efficacy, and achievement, ultimately supporting evidence-based strategies to enhance student success.

Keywords: Machine Learning Model, Test Anxiety, Academic Achievement, Multi-Layer Perceptrons, Prediction Model.

1. INTRODUCTION

Advancements in machine learning (ML) and artificial intelligence (AI) have significantly transformed healthcare education, improving efficiency, accuracy, and standardization in patient data analysis. AI and ML-based models enable the development of predictive tools that forecast future outcomes, facilitating data-driven decision-making and strategic planning. ML involves training algorithms to perform human-like tasks, such as decision-making, speech recognition, and pattern recognition [1].

The development of predictive models using machine learning (ML) and artificial intelligence (AI) enables the identification of at-risk patients and the creation of early preventive solutions [2]. Similarly, analyzing psychological variables in academic settings can provide insights into students' cognitive and behavioral traits, which shape their future development. However, factors such as test anxiety, self-efficacy, academic achievement, fear of tasks, and perceptions of future challenges can negatively impact students' personal and academic growth, often leading to dropout or disengagement [3, 4]. These factors undermine motivation and commitment, highlighting the need to address both academic and personal variables to fully understand the learning process.

To address these challenges, studies should focus on identifying skill gaps and strategies for meeting academic demands, enabling the development of effective mathematical models to analyze these factors and create plans that enhance student efficiency while mitigating disadvantages. Albert Bandura's social cognitive theory emphasizes the role of self-efficacy—an individual's belief in their ability to achieve specific goals—as a key determinant of motivation, behavior, and achievement. Individuals with high self-efficacy are more likely to pursue challenging tasks, persist through obstacles, and achieve success, while those with low self-efficacy may avoid challenges, give up easily, and feel inadequate [5]. Factors influencing self-efficacy include past experiences, social support, and verbal persuasion, with positive feedback and encouragement strengthening these beliefs [6].

Test anxiety, characterized by nervousness or emotional distress during exams, can hinder academic performance, while academic achievement reflects a student's ability to overcome adversity, adapt to challenges, and persist despite setbacks such as difficult coursework or poor grades [7]. Understanding and addressing these factors is essential for fostering student success and well-being.

According to the current studies about the test anxiety, self-efficacy, academic achievement, the following are the main points that examine the student performance:

- Develop effective mathematical models: To analyze these factors and conclude plans to improve student efficiency, personal and academic factors and the lack of skills and strategies to deal with academic requirements must be studied. Self-efficacy is the conviction that one can accomplish a specific goal, can significantly influence motivation, behavior, and achievement. Several factors, including past experiences, social support, and verbal persuasion, can contribute to self-efficacy. Test anxiety, academic achievement, and overcoming obstacles and adversity are critical factors that impact student performance.

- Examine Test anxiety: Test anxiety refers to the feelings of nervousness, worry, and stress that students experience before, during, or after taking an exam.
- Supportive factors: Some helpful factors lead a person to reduce anxiety about tests, including fear of failure and pressure from others. On the other hand, Academic achievement can increase the student's ability to persevere to overcome academic challenges. Here we can mention some factors contributing to raising Academic achievement, including cognitive thinking, thinking about achieving the goal, and social support.
- Academic achievement: The percentage of test anxiety increases with a decrease in Academic achievement, which makes students suffer academically more than others. Therefore, the institution and the home should be aware of these challenges and find ways to mitigate them with moral and material support and resources, which helps the students overcome anxiety in tests and achieve better results.

This study explores ways to understand the impact of Academic achievement and test anxiety on student achievement by applying a mathematical model based on machine learning and neural networks. The study also sheds light on understanding the personal and academic factors that affect achievement and academic performance, analyzing them using mathematical models, and extracting the relationship that links the model variables to develop strategic plans to improve academic performance.

2. LITERATURE SURVEY

The comparison between traditional methods and modern approaches, such as ML, highlights the superior capabilities of ML in analyzing large datasets and identifying complex relationships between variables. Unlike traditional methods, ML improves the accuracy of feature selection, effectively handles missing or unseen data, and generalizes results more efficiently. These advantages make ML a powerful tool for deriving meaningful insights and informing decision-making in survey research, demonstrating its clear superiority over conventional approaches in addressing modern analytical challenges.

Several studies have explored the relationship between test anxiety and academic motivation as mediators to improve student performance (FIGURE 1). Fatih and Dadadi (2020) [8] investigated the connection between academic self-efficacy and performance using test anxiety and academic motivation as mediators. Their study involved 387 high-school students in Trabzon, Turkey (201 males and 186 females). The results revealed statistically significant correlations between academic motivation and test anxiety, which influenced the relationship between academic achievement and self-efficacy. Nursing students, who undergo extensive training for a demanding profession, often face significant stress. Robson et al. emphasized that anxiety can be managed, and self-efficacy beliefs regulate motivation and behavior. Self-efficacy theory has significantly contributed to understanding human motivation, with research showing that motivational outcomes and achievement are strongly influenced by self-efficacy [9]. A study in [10] focused on test anxiety in elementary school children aged 5 to 12. After reviewing 76 research papers, the authors found that girls in Asian samples experienced higher levels of test anxiety compared to boys and samples from Europe and North America. The study recommended more experimental research to reduce test anxiety among primary school children.

The COVID-19 pandemic (2020–2022) significantly impacted individuals with underlying medical conditions, healthcare professionals, and elderly adults. According to the World Health Organization, the pandemic caused widespread fear, worry, and concern globally. A study conducted in Greece post-COVID-19 examined the emotions, self-efficacy, and achievement of university students from families with SEND (Special Educational Needs and Disabilities) [11]. Nursing students, in particular, are prone to depression, as highlighted in several studies [12, 13]. Their perception of stress greatly influences their mental health, academic performance, and overall well-being. Stress can lead to anxiety, depression, and even suicidal thoughts among nursing students [14, 15]. Luo (2019) [16], explored how self-compassion can reduce depression and anxiety in nursing students. They proposed a machine learning model based on structural equation modeling (SEM) to analyze the relationship between self-compassion, perceived stress, anxiety, and depression. The study involved 1,453 nursing students in Ningbo, China, and found that self-compassion significantly reduced anxiety and depression under stress.

Devi (2021) [17], emphasized that nursing students are at high risk of stress, depression, and anxiety, which can negatively affect their academic performance and well-being. Achievement, defined as the ability to handle and recover from stressful situations, plays a critical role in mitigating these effects. Understanding how achievement buffers the relationship between stress, depression, and anxiety is essential for supporting Indonesian nursing students. High stress levels can significantly impact academic performance and self-efficacy. Building self-efficacy is crucial for academic success, and students can achieve this by setting realistic goals, adopting a growth mindset, seeking support, and prioritizing physical and mental health. Hitches (2022) [18], demonstrated that academic self-efficacy is a key predictor of college success in their study of 305 Australian university students. Stress, however, can undermine this ability. Self-care activities and exercise help students manage stress and maintain a positive attitude. Universities must provide resources and skills to support students under stress.

MLP models have been increasingly applied in educational research to analyze complex relationships between psychological, behavioral, and academic factors. Alomari et al. (2022), [20] employed MLP models to forecast student academic performance, focusing on variables such as study habits, attendance, and psychological well-being. By training the MLP model on data from a Jordanian university, the researchers successfully classified students into performance tiers (e.g., high, medium, low) and achieved superior predictive accuracy compared to traditional statistical approaches like linear regression. The study highlighted the MLP's ability to uncover nonlinear relationships, particularly the significant role of psychological factors such as motivation and stress in shaping academic outcomes. The model identified study habits and psychological well-being as critical predictors of performance, reinforcing the value of these factors in academic success. The researchers concluded that MLP models are highly suitable for educational research, given their capacity to model complex interactions and generate accurate predictions. This mirrors the current document's use of MLP to investigate the impact of test anxiety and self-efficacy on academic achievement, showcasing the model's effectiveness in analyzing multifaceted educational datasets. Zhang et al. [19] used MLP models to examine how emotional factors, such as anxiety and self-efficacy, influence student learning outcomes. The researchers gathered data from Chinese high school students and applied MLP to analyze the relationship between emotional states and academic performance. The MLP model successfully identified critical emotional factors, including test anxiety and motivation, that played a significant role in shaping learning outcomes. The study highlighted the MLP's ability to model nonlinear interactions, providing insights into how emotional states impact academic success. Key findings indicated that high levels of test anxiety negatively affected performance, while self-efficacy had a positive influence. The study emphasized the MLP model's effectiveness in educational research, particularly for analyzing complex psychological and emotional factors. This work complements the current document's exploration of the relationship between test anxiety, self-efficacy, and academic achievement, reinforcing the value of MLP models in understanding the dynamics of student performance.

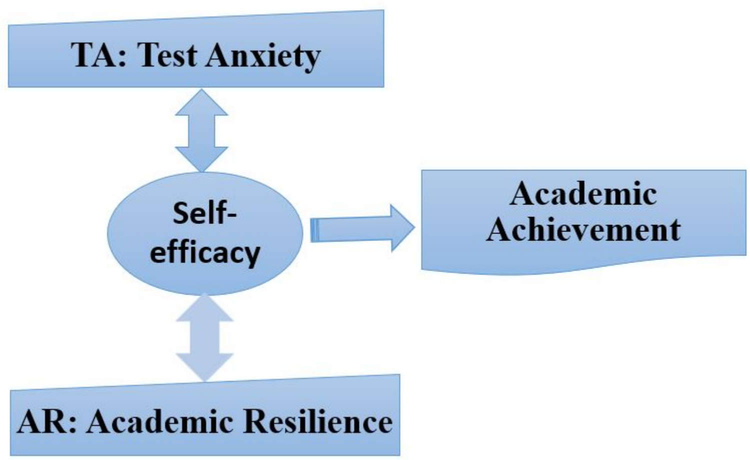

Figure 1: Relationship between test anxiety, and academic achievement

This study aims to identify strategies for reducing test anxiety, investigate the impact of self-efficacy on achievement, explore the relationships between self-efficacy, test anxiety, and academic achievement, and develop predictive models to simulate these behaviors. The goal is to enhance understanding and support improvements in student outcomes. TABLE 1 summarizes the findings and outcomes of research on academic achievement, self-efficacy, and test anxiety.

3. RESEARCH METHODOLOGY

The relationship between academic achievement, test anxiety, and self-efficacy was analyzed and explored in this publication using both qualitative and quantitative research approaches. SPSS software version 25 was used to calculate and compare the qualitative data. The link between the quantitative data (input datasets and their target) is analyzed and measured by the fully connected feedforward multilayer perceptron network. Google Forms was utilized to send a well-structured questionnaire online in order to gather qualitative data.

Table 1: summarizes studies results and findings on test anxiety, self-efficacy and academic achievement

Authors	Country	Sample Size	Factors of comparison	Findings
Alomari [20]	Jordan	University students (exact size not specified)	Study habits, attendance, psychological well-being (e.g., motivation, stress)	MLP models outperformed traditional methods like linear regression in predicting academic performance.Psychological factors (e.g., motivation, stress) significantly influenced academic outcomes.Study habits and psychological well-being were key predictors of performance.
Zhang [19]	China	High school students (exact size not specified)	Emotional factors (e.g., test anxiety, self-efficacy, motivation)	MLP models effectively captured nonlinear relationships between emotional factors and academic performance. High test anxiety negatively impacted performance, while self-efficacy had a positive effect.MLP models are highly effective for analyzing complex psychological and emotional factors in educational research.
Hitches [18]	Australia	305 university students	Academic self-efficacy was negatively impacted by stress, with higher levels of stress leading to lower levels.	Academic self-efficacy is one of the most important predictors of success in college. The findings shows that stress can undermine this ability. Self-care activities and exercise can help students cope with stress and maintain a positive attitude.
Devi [17]	Indonesian	336 nursing students	|Nursing students facing more stress and higher levels of depression and anxiety. Achievement is impacted stress-anxiety.	Researchers suggest achievement can buffer the adverse effects of stress on mental health outcomes such as depression and anxiety. To support the well-being of their students, nursing schools might consider integrating achievement training into their curricula. Problem-solving, emotion regulation, and positive thinking are some skills developed in achievement training to deal with stress and adversity.
Luo [16]	China	1453 nursing students	Self-compassion helps decrease students' anxiety and depression under stress.	Nursing students can manage their stress and prevent anxiety and depression by practicing self-compassion. It has been proven that self-compassion has numerous benefits for mental health, such as kindness, understanding, and acceptance. Self-compassion training may be incorporated into nursing schools to support students.
Van der Riet [15]	Australia	14 undergrad-uate nursing students	Stress levels of the students decreased and their ability to manage stress improved.	Several insights were gleaned from the study's implementation of a stress management and mindfulness program. Three important lessons were learned: the need for ongoing support, the importance of program evaluation, and the importance of flexibility in programs. The study suggests that such programs can help students feel more connected, reduce stress, and improve well-being.

Table 1: Continued..

Authors	Country	Sample Size	Factors of comparison	Findings
Kulsoom [14]	Saudi Arabia	575 medical students	The medical students are despondent, worried, and under a lot of stress. Compared to their male peers, female medical students had higher levels of stress, anxiety, and depression.	Medical students' academic workload, financial strain, lack of social support, and sleep deprivation are all factors linked to stress, anxiety, and depression. Anxiety symptoms were reported by 60.5% of individuals, depression symptoms by 45.5%, and stress symptoms by 56.7% of people. Compared to their male peers, female medical students had higher levels of stress, anxiety, and depression.
Cheung [13]	Hong Kong	661 nursing students	High prevalence of depression, anxiety, and stress among nursing students.	The study found that nursing students in Hong Kong suffer from depression, anxiety, and stress symptoms. 43.1% suffer from depression, 61.9% suffer from anxiety, and 60.8% suffer from stress. Anxiety, stress, and sadness were more prevalent among female nursing students. It is recommended that interventions should reduce the academic workload among nursing students, provide financial support, and promote social support.
Papazisis [12]	Brazilian	169 undergraduate nursing students	Self-esteem partially mediates anxiety and depression's relationship with religious and spiritual beliefs.	Nursing students' self-esteem is favorably connected with their religious and spiritual views. Moreover, religious and spiritual beliefs were negatively related to anxiety and depression. They indicate that religious and spiritual beliefs may protect nursing students from adverse mental health outcomes
Tsibidaki [11]	Greece	61 parents and caregivers of individuals with special educational needs and disability	The levels of anxiety were negatively related to meaning in life, self-efficacy, and achievement.	The COVID-19 pandemic has negatively impacted the mental well-being of families and children with special educational needs. The article illustrates the importance of supporting and empowering these families to facilitate their achievement and self-efficacy to alleviate anxiety and improve outcomes. Healthcare providers and community organizations should develop tailored interventions to support families and students during the crisis by considering their unique needs.
Fatih [8]	Turkey	387 high-school students	Significant correlations between academic motivation and test anxiety.	The results show statistically significant correlations between academic motivation and test anxiety, affecting the relationship between self-efficacy and academic performance.

TABLE 2 presents the independent and dependent variables used to examine the relationship between test anxiety and academic achievement. The independent variables (TA1–TA10) focus exclusively on various aspects of test anxiety, such as nervousness before exams, difficulty concentrating, and the impact of anxiety on performance. These items measure the extent to which students experience anxiety during testing situations. On the other hand, the dependent variables (AR1–

AR5) are related to academic achievement, reflecting students' strategies and emotional responses to academic stress, such as setting goals, self-imposing rewards or penalties, and coping with stress. However, the table does not include independent variables related to self-efficacy, which refers to a student's belief in their academic abilities, nor does it include dependent variables directly measuring academic achievement, such as exam grades or overall academic performance. To fully align with the study's objective of analyzing how self-efficacy and test anxiety affect academic achievement, the table should be expanded to incorporate self-efficacy as an independent variable and academic achievement as the primary dependent variable.

Table 2: Independent and dependent variables to examine the test anxiety

Independent variables	**Dependent variables**
TA1: *I have visible signs of nervousness (sweaty palms, shaky Hands, etc.) on right before a test*	AR1: My goal is to stop thinking negatively.
TA2: *Does anxiety in the test affect your performance in the test?*	AR2: I would set a plan to achieve my goals.
TA3: *Exam anxiety makes it difficult to focus on the exam and perform properly.*	AR3: I would self-impose rewards and penalties based on my output.
TA4: *Does exam anxiety hinder focus on the exam, which negatively affects performance?*	AR4: I would probably get depressed because of the stress.
TA5: *Exam anxiety continues with me even after the end of it, and I cannot forget or stop it.*	AR5: I would begin keeping up with my efforts and accomplishments.
TA6: *It is hard for me to sleep the night before the test*	
TA7: *Some students are more nervous than others during exams, affecting their performance.*	
TA8: *Anxiety makes me feel unable to answer the questions when I read them.*	
TA9: *Feel worried before and during the exam*.	
TA10: *Consistently, I remembered past reactions while preparing for a test.*	

The analytical results will help decision-makers and institution managers develop effective strategies and practical solutions to reduce the effects of exam anxiety. This will help the student to achieve the highest achievement and improves the academic results of students. Therefore, using a mathematical model based on the idea of a neural network—which mimics the human mind by addressing such a relationship—the current study aims to investigate and analyze the impact of the relationship between self-efficacy and test anxiety on the academic achievement of the students. Two research questions will be addressed in order to carry out the study's objectives: (1) What is the relationship between self-efficacy and test anxiety and its impact on academic achievement? And (2) How can mathematical models through machine learning identify the variables that affect raising the percentage of academic achievement?

4. MACHINE LEARNING METHOD DESIGN

Many models of neural networks, including single-layer or multi-layer networks, exist. Since this study aims to study multiple variables that affect the current problem system, a multi-layer neural network (MLP) that provides learning of complex patterns has a great potential to elucidate the relationship between the processed data. Therefore, MLP is applied to measure and analyze the effect of self-efficacy and test anxiety on student achievement. MLP is a powerful tool for extracting insights and understanding the underlying patterns and dynamics in survey data, its deployed to examine the relationship between test anxiety and academic achievement. MLPs are often used in data classification applications and forecasting rates of future outcomes, so MLP is applied to analyze data accurately for medical conditions and mental disorders. [21]. MLP consists of multiple interconnected layers of neurons from input to output and is interconnected by hidden layers. The input layers are used to enter the data and convert it into digital data based on calculating the weight for each variable and transferring the data to the hidden layers after obtaining the necessary activation value after a series of calculations to reach the highest weight value. In contrast, the output layer helps to display the final information after the end of training to obtain the classifications of the last changes or values of the regressions [22]. Each neural layer in the MLP has input variables, and each input variable has a self-calculated or randomly assigned weight. Through the learning process, the values of the weights are updated. In order to finish training the network, we need a specific learning algorithm. The most popular is the backpropagation algorithm which adjusts the weights of each input by calculating the gradient of the loss function and updates it accordingly [23]. Iterative training of variables in MLP allows us to improve the network's performance and make accurate predictions based on the input data representing the actual experiment values. In order to perform well with the computation model, we have to use a large amount of data in simulating the experiment data, which is computationally expensive.

One of the advantages of using an MLP neural network is to train on fewer data to reduce computational costs. Therefore, the study aims to take advantage of the ability of the multi-layered neural network model to capture the complex relationships between the input variables, such as self-efficacy and test anxiety, and the output variable, such as academic achievement. One of the expected results of the study is to provide an analysis and calculation of the relationship between self-efficacy, test anxiety, and the student's academic achievement percentage [24]. This contributes to the development of systems and strategies to support students in managing and overcoming test anxiety and enhance self-efficacy to reduce anxiety, thus improving student academic results.

The current experiment used an MLP neural network with ten input layers, one hidden layer, and five output layers based on the current problem data. The present network has implemented hyperbolic tangent arithmetic ("tanh") as an activation function in order to compute the nonlinear value of set input values within a range of -1 to 1. "tanh" is a symmetric function with equal positive and negative values around zero that helps avoid computation bias. The sum of squares function is used to measure the error of the calculation. The data was divided into two parts to develop the machine learning model: the training sets to complete the training of the network and the test sets to evaluate the model's performance. In this experiment, the data set was divided into 67.8% (179) of the total data for the training set, and the remaining 32.2% (85) is for the test set. The MLP topology is illustrated in FIGURE 2.

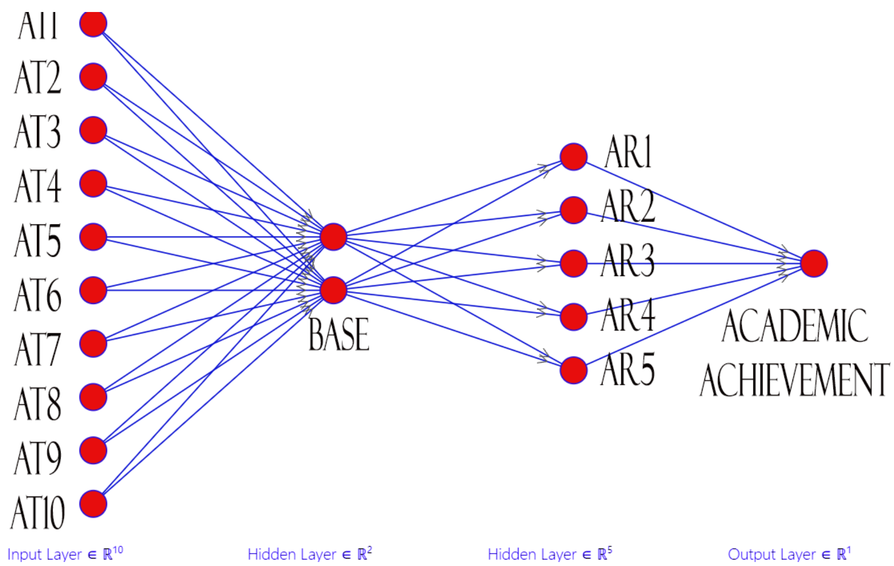

Figure 2: Proposed MLP topology

To accurately address one of the research gaps by capturing complex nonlinear relationships between variables, this study employs MLP to investigate the connection between test anxiety, academic achievement, and academic achievement. Unlike traditional statistical methods, which are limited to solving linear relationships, MLP can simulate complex and nonlinear interactions between variables. One of the key advantages of MLP models is their ability to learn and train effectively even with fewer nonlinear patterns, making them particularly suitable for studying psychological concepts like academic achievement and test anxiety, which often exhibit dynamic and nonlinear behaviors. Additionally, MLP models can efficiently learn relationships between feature data, such as academic achievement, test anxiety, and academic achievement. Furthermore, MLP models have demonstrated excellent predictive power across various disciplines, offering high prediction accuracy that enables precise forecasting of academic achievement based on characteristics related to test anxiety and academic achievement.

This section outlines the use of a MLP neural network with 10 input layers, 1 hidden layer (number of neurons unspecified), and 5 output layers, employing the hyperbolic tangent ('tanh') activation function to handle nonlinear data within the range of -1 to 1. The sum of squares function is used for error measurement, and the backpropagation algorithm is applied for weight updates. The dataset is split into 67.8% (179 samples) for training and 32.2% (85 samples) for testing. However, key hyperparameters such as the learning rate, number of neurons in the hidden layer, number of epochs, batch size, optimization algorithm, and any regularization techniques are not specified, which are crucial for reproducibility and a comprehensive understanding of the model's training process.

The network output is computed as in equation (1).

$$\text{W-net} = \int_{i=1}^{n} w_i * x_i \tag{1}$$

where x_i is the input vector to the network and w_i is the weight of each input i.

The backpropagation learning algorithm (BP) is utilized to adjust errors across network layers and modify weights in the hidden layer. The computation of the BP learning function is defined as in equation (2)

$$\mathrm{E(w)} = \int_{p=1}^{pt} \int_{i=1}^{epoch} (\mathrm{di}(p) - \mathrm{yi(p)})^2 \tag{2}$$

where E (w) is the error function, w is the weight vector. di(p) is desired output of neuron I and yi(p) is experimental output of the neuron i.

The weight is computed as in equation (3):

$$Wij\ (n+1) = Wij\ (n) + \eta\delta i\ (n) + x\mathrm{j}(n) \tag{3}$$

Where the $\delta i\ (n)$s is the computed local error based $Wij\ (n)$ using step size is η.

Equation (4) provides the hyperbolic tangent function, which is usually expressed as "tanh(x)":

$$\tanh\mathrm{(x)} = (e^x - e^{(-x)})/(e^x + e^{(-x)}) \tag{4}$$

The equation uses "e" to represent Euler's number, approximately 2.71828. The hyperbolic tangent function converts any real number input "x" into a value between -1 and 1, creating a sigmoid curve. This curve is symmetric around the origin (0,0) and approaches 1 when "x" approaches positive infinity and approaches -1 as "x" approaches negative infinity.

5. RESULTS AND DISCUSSION

This section shows how the suggested approach based on the machine learning model is applied using multilayer neural networks (MLP) to test the effect of factors of Academic achievement and exam anxiety on academic achievement. The neuronal model (MLP) was applied because it is an effective method for learning complex patterns, analyzing them, and predicting the results accurately because of its ability to classify factors according to their importance in the model. The results of the study are discussed and analyzed statistically to ensure the validity of the data and to extract patterns of relationships later [25]. Then we discuss the results of applying the MLP multilayer neural model to test students' academic achievement based on the inputs of the value of Academic achievement and test anxiety. In order to collect the necessary data for the research, a questionnaire was created and distributed online to a sample of students containing a set of questions to calculate the relationship between Academic achievement, test anxiety, and academic achievement. The statistical results showed the strength of the correlation between the input and the output variables.

6. DATA COLLECTION

The study used data collected through a questionnaire distributed online to students. The validity and accuracy of the data and the relationships between the variables were tested by applying different statistical techniques using SPSS, such as correlation analysis and regression [26]. This data underwent a comprehensive and rigorous cleaning and filtering process to ensure data quality and suitability for the study. The reconfiguration steps included repairing structural errors, cleaning, removing duplicate or incomplete data that is missing part of the necessary information or missing data sets, and deleting unwanted data sets. More than 400 students participated in the survey after it was delivered to them; they presented honest and truthful answers based on their opinions and their voluntary participation. After cleaning the data and isolating the defective ones, we obtained only 264 participants who met the study requirements and were included in the final clean, high-quality data set that provided reliable and accurate information for the study and contributed to producing accurate results.

6.1 Statistical Results

Various statistical methods are used in analyzing data and examining the relationship and distribution of variables, such as mean, median, and mode. It can provide helpful information about the average value of the data and center point [27, 28].

The mean of the datasets is the sum of all the values (x_i) divided by the total number of data (n) as represented in equation (5).

$$\text{Mean}(\mu) = \int_{i=1}^{n} (x_i)/n \tag{5}$$

The Median determines the middle value by arranging the dataset in ascending or descending order. If the total number of data is even, then the Median is the arithmetic mean of the two middle values. Standard deviation describes measures of the distribution of a dataset comparable to its mean, which is calculated by the equation [6]

$$\text{Standard Deviation } (\sigma) = \sqrt{(\sigma^2)} \tag{6}$$

The average of the squared data deviations from the arithmetic mean is determined by the variance. It is computed using the formula [7].

$$\sigma^2 = \left(\sum_{i=1}^{n} (x_i - \mu)^2\right)/n \tag{7}$$

The results of this study show that the mean value is 3.51 and the median value is 4, which indicates that the data tend to cluster. The values of standard deviation and variance are 1.14 and 1.3, respectively. Skewness measures the asymmetry of the data, which is equal to 0.15. Moreover, the data's peak degree is measured by the kurtosis, which equals -0.125—finally, determining the minimum and maximum values equal to 1 and 5, respectively. The results are depicted in TABLE 3, shows that the mean value is identical to the median value, which indicates that the data are relatively symmetrical distributed—this symmetry of data help to enhance the accuracy of central tendency representation, simplifying data interpretation (FIGURE 3).

6.2 Neural Network Model Results

This experiment includes four factors to describe academic achievement toward reaching the objectives of this study. The first factor is AR1, which highlights the importance of keeping a positive attitude and stopping negative thinking with a rate of importance equal to 0.997. This factor is one

Table 3: Statistics descriptive results

		Gender	Age	TA1	TA2	TA3	TA4	TA5	TA6	TA7	TA8	TA9	TA10
N	Valid	264	264	264	264	264	264	264	264	264	264	264	264
	Missing	0	0	0	0	0	0	0	0	0	0	0	0
Mean				3.51	4.05	4.31	3.67	3.54	3.61	3.65	3.64	3.65	3.39
Median				4	4	5	4	4	4	4	4	4	3
Std. Deviation				1.14	1.081	0.952	0.957	1.266	1.298	1.346	1.193	1.17	1.119
Variance				1.3	1.169	0.907	0.915	1.603	1.684	1.811	1.424	1.369	1.251
Skewness				-0.546	-1.073	-1.323	-0.156	-0.525	-0.633	-0.639	-0.46	-0.614	-0.331
Std. Error of Skewness				0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15
Kurtosis				-0.125	0.61	1.061	-0.587	-0.726	-0.645	-0.773	-0.671	-0.326	-0.51
Std. Error of Kurtosis				0.299	0.299	0.299	0.299	0.299	0.299	0.299	0.299	0.299	0.299
Minimum				1	1	1	1	1	1	1	1	1	1
Maximum				5	5	5	5	5	5	5	5	5	5

of the most critical factors for success because negative thoughts can increase self-doubt and low self-efficacy, which hinder academic achievement. The next factor is AR2, which emphasizes the importance of a well-thought-out strategy to achieve the objective. TABLE 4 shows the results of the MLP Model Summary with 1000 epochs. The AR2 is a crucial factor that shows the need for students to make a plan to achieve their goals.

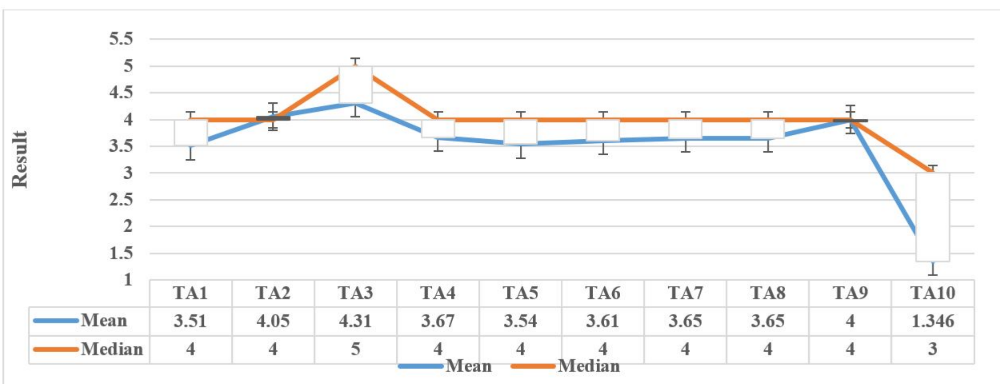

Figure 3: Statistics descriptive results

The results show it is a crucial factor based on the important rate, which equals 0.981. Also, the third factor AR3 is crucial based on the important rate, which equals 0.980. Besides the fourth factor, AR4 indicates the negative impact of stress on increasing depression with an important rate equal to 0.779. Finally, the AR5 factor indicates that the students are willing to adjust their plan to achieve their goal, with a value of importance equal to 0.996. These four factors reflect a mindset of determination, self-awareness, and adaptability crucial for success in any endeavor.

To answer the first research question "RQ1: What is the relationship between self-efficacy and test anxiety and its impact on academic achievement?"

Table 4: MLP Model Summary with 1000 epochs

Training		Sum of Squares Error	106.997
		Average Overall Relative Error	.716
	Relative Error for Scale Dependents	My goal is to stop thinking negatively.	.715
		I would set a plan to achieve my goals.	.679
		I would self-impose rewards and penalties based on my output.	.732
		I would probably get depressed because of the stress.	.678
		I would begin keeping up with my efforts and accomplishments.	.808
		Training Time	0:00:00.02
Testing		Sum of Squares Error	50.138
		Average Overall Relative Error	.940
	Relative Error for Scale Dependents	My goal is to stop thinking negatively.	.997
		I would set a plan to achieve my goals.	.981
		I would self-impose rewards and penalties based on my output.	.980
		I would probably get depressed because of the stress.	.779
		I would begin keeping up with my efforts and accomplishments.	.996

The results of the neural network model related to testing anxiety and how it affects individuals' performance before and during an exam. The first factor, AT1, describes visible signs of nervousness, such as sweaty palms and shaky hands, before a test, considered moderate with an important rate of 0.146. The second factor, AT7 factor states that some students are more prone to nervousness during exams, which ultimately affects their performance with rate of 0.126. The third factor is AT10, describes how past experiences can affect an individual's preparation and readiness for an upcoming test, and it has a moderate importance rate of 0.122. The factor, AT6, highlights how difficult it is for some individuals to sleep the night before a test due to anxiety. It has a lower importance rate than the others (AT1, AT7, and AT10). Also, the factor, AT8, presents the impact of anxiety to make student feel unable to answer the questions when read them. It has a lower importance rate than the others (AT1, AT7, and AT10). The factors (AT2, AT3, AT4, AT5, AT6, and AT9) are the less impactful and important on the student achievement.

Finally, Overall, these results shed light on how test anxiety can manifest itself and affect academic achievement. Utilizing different numbers of epochs in the experiments when training an MLP neural network model can provide several benefits, allowing researchers to assess the model's performance and optimize its learning process. We implemented different numbers of epochs in MLP neural network experiments, which offers valuable insights into the model's performance, convergence, generalization, and stability. This helped us optimize the training time, avoid overfitting, and fine-tune the hyperparameters. It is important to note that the optimal number of epochs can vary depending on the dataset's complexity, size, and the complexity of the modeled relationships. In some cases, increasing the number of epochs beyond a certain point can lead to overfitting, where the model becomes too specialized in the training data and fails to generalize well to new, unseen data. Thus, striking the correct balance is essential, and determining the ideal number of epochs for a given problem frequently calls for experimentation and validation methods like cross-validation.

Our findings in TABLE 5, show that choosing the right number of epochs may significantly enhance the model's performance and ensure that it can correctly identify the most important features. The first experiment had unstable and inconsistent results when 10 epochs were used as shown in FIGURE 4. This was due to the neural network's node weights not having enough time to adjust and accurately reflect the patterns in the data. During training, the neural network updates its weights to minimize the difference between predicted outputs and actual targets. The model needed more iterations to converge and arrive at an ideal answer since there were only a certain amount of epochs. Increasing the number of epochs gives the model more training time to fine-tune its weights and improve its ability to recognize patterns. This iterative process allows the neural network to adjust its parameters more accurately and align them with the desired data representation. Consequently, the model becomes more stable and consistent in its predictions, producing more reliable and robust results. The choice of 1000 epochs as the optimal setting is justified by the model's improved stability, convergence of error metrics, and the stabilization of importance rates for key factors. At 10 epochs, the model was underfitted, producing unstable results with low importance rates for key factors like AT1 (0.108). As the number of epochs increased to 50 and 100, the model showed improvement, but the importance rates (e.g., AT1 at 0.144 and 0.131) were still lower than at 1000 epochs. By 1000 epochs, the model achieved the highest importance rates for key factors (e.g., AT1 at 0.146, AT7 at 0.126, AT10 at 0.122), indicating it had fully learned significant patterns without overfitting. Additionally, the sum of squares error for the training set (106.997) and testing set (50.138) at 1000 epochs suggests a balance between learning and generalization, making 1000 epochs the optimal choice for model performance.

Table 5: Independent Variable Importance

Importance/ #Epochs	AT1	AT2	AT3	AT4	AT5	AT6	AT7	AT8	AT9	AT10
10	.108	.098	.087	.062	.069	**.139**	**.133**	**.146**	.078	.081
50	**.144**	.077	.084	.092	.080	.113	**.125**	.111	.058	**.117**
100	**.131**	.076	.091	.084	.087	.106	**.124**	.091	.082	**.117**
1000	**.146**	.091	.085	.073	053	.087	**.126**	.121	.096	**.122**

TA1: I have visible signs of nervousness (sweaty palms, shaky Hands, etc.) on right before a test
TA2: Does anxiety in the test affect your performance in the test?
TA3: Exam anxiety makes it difficult to focus on the exam and perform properly.
TA4: Does exam anxiety hinder focus on the exam, which negatively affects performance?
TA5: Exam anxiety continues with me even after the end of it, and I cannot forget or stop it.
TA6: It is hard for me to sleep the night before the test
TA7: Some students are more nervous than others during exams, affecting their performance.
TA8: Anxiety makes me feel unable to answer the questions when I read them.
TA9: Feel worried before and during the exam.
TA10: Consistently, I remembered past reactions while preparing for a test.

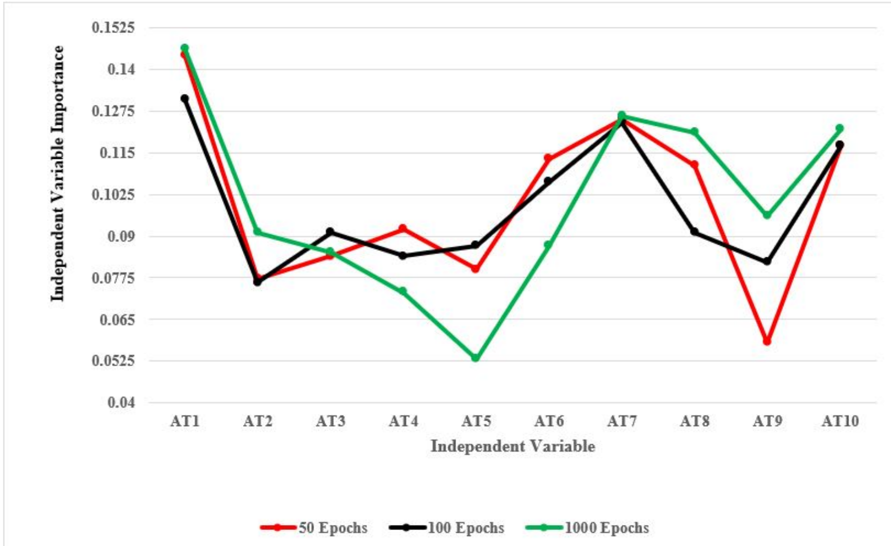

Figure 4: MLP results of importance variable level for (50,100,1000) epochs

RQ2: How can mathematical models through machine learning identify the variables that affect raising the percentage of academic achievement?

Using a machine learning approach called Multilayer Perceptron (MLP), we aimed to identify distinct patterns in academic achievement and test anxiety factors that affect academic achievement in different student groups. Specifically, we focused on two groups: Group 1, which comprises students who are nervous during exams, and Group 2, consisting of students who have experienced past exam reactions.

Based on these considerations, we can conclude that the factor AT1: "I have visible signs of nervousness (sweaty palms, shaky Hands, etc.) on right before a test", significantly impacts academic achievement. Test anxiety can hinder students' academic progress by reducing their ability to perform their fullest potential during exams. It is follows by the factor AT7: "Some students are more nervous than others during exams, affecting their performance," mainly impacts academic achievement. While the factor "AT10: Consistently, I remembered past reactions while preparing for a test" can provide insight into the impact of past experiences on students' test preparation and performance, it should be used in conjunction with other measures to provide a comprehensive understanding of the factors that influence academic achievement.

Our findings can inform educators and policymakers in developing targeted interventions that cater to the unique needs of these student populations and lead to improved academic outcomes.

Based on the MLP results after 1000 epochs, FIGURE 5 displays the importance variable level. It is evident that AT1, AT7, AT10, and AT8 are the most significant impact factors.

Mathematical prediction models help people make better decisions, anticipate future outcomes more efficiently, understand relationships, and optimize processes. These tools are valuable for decision-makers and researchers in various fields. A polynomial model is a mathematical formula that uses

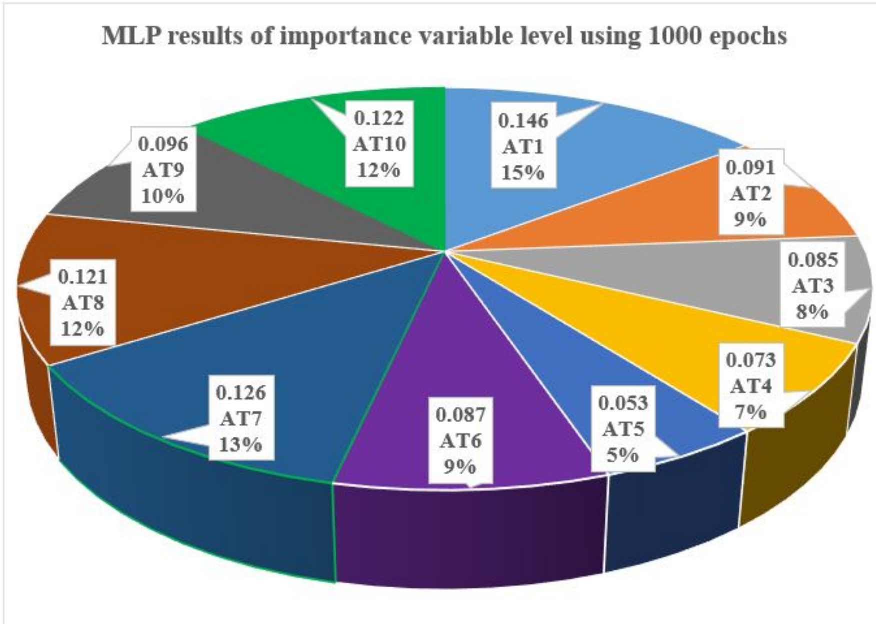

Figure 5: MLP results of importance variable level using 1000 epochs

polynomial words to illustrate the link between an independent variable ('x') and a dependent variable ('y'). These terms are obtained by multiplying the powers of the independent variable by coefficients. Polynomial models are a powerful tool for predicting experimental data, especially when the relationship between variables is nonlinear [26]. In the polynomial model, the independent variable (x) is inferred to be factors related to test anxiety (e.g., visible signs of nervousness, difficulty sleeping before exams) or self-efficacy (e.g., students' belief in their ability to succeed), while the dependent variable (y) is likely academic achievement, measured by grades, test scores, or performance metrics. The model uses a fifth-degree polynomial to predict outcomes, with the coefficient of determination (R^2) indicating how well the independent variable explains the variance in academic achievement. Although the document does not explicitly define these variables, the context of the study, which focuses on the impact of test anxiety and self-efficacy on academic performance, supports this interpretation.

Our model uses the fifth degree of the polynomial to make effective predictions and gain insight from experimental data. A statistical metric known as the coefficient of determination, or R2, indicates the percentage of the variance in the dependent variable (y) that can be accounted for by the independent variable (x) in the model. FIGURE 6 shows that the value of 1 for R^2 indicates a perfect fit, meaning that the independent variable accounts for most of the variance in the dependent variable.

Predicting experimental data in advance for 5 or 10 years is crucial because it may provide several advantages, including strategic planning, long-term analysis and implementation, and accurate decision-making. However, it is necessary to clarify that the prediction of empirical data for future years is approximate values that may include errors due to rounding or cutting the results of calculations such as division and multiplication. Such unanticipated mathematical errors may cause future events and conditions to deviate from original expectations or results.

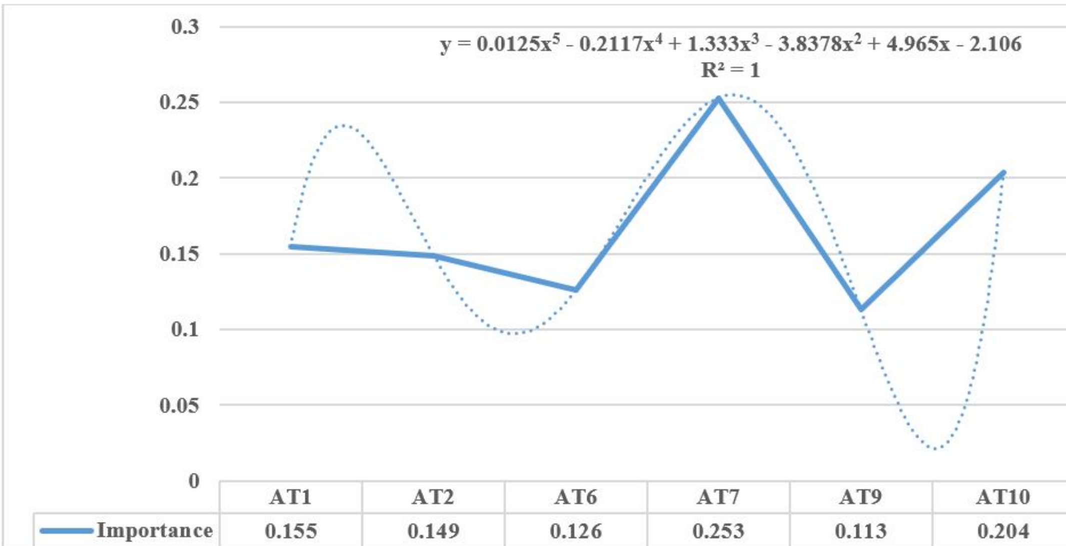

Figure 6: Polynomial models of fifth degree

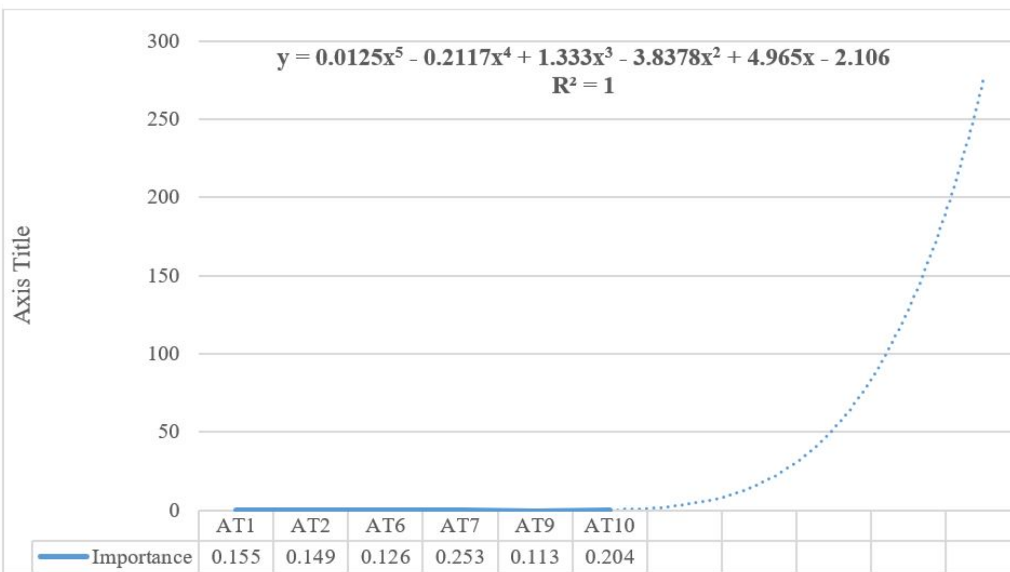

Figure 7: The Prediction models of future figures

FIGURE 7 shows that the future prediction of self-test anxiety increased by 300% in the next 5 years, affecting academic achievement. Therefore, the students who get more nervous during exams will be more affected by test anxiety based on the results of the factor (AT7). Additionally, the study indicates that the student's bad past experiences with testing may impact a student's preparation for the current exam and affect overall performance based on the result of the factor (AT10). The future values of the independent variables (e.g., test anxiety factors) used in the prediction process were likely obtained through extrapolation of historical trends, assumptions about future changes, and possibly external data. The polynomial model, trained on historical data, was applied to a future time horizon (e.g., the next 5 years) by extending the time variable and assuming that the relationships between the independent variables (e.g., visible signs of nervousness, difficulty sleeping before exams) and the dependent variable (self-test anxiety) would continue to follow the same patterns. The model predicted a 300% increase in self-test anxiety over the next 5 years, reflecting the projected trends in the independent variables and the mathematical relationships captured by the polynomial equation. This process allowed the model to forecast future anxiety levels based on the input data and assumptions.

7. CONCLUSION

This study employed a multi-layer perceptron (MLP) machine learning model to identify key factors influencing academic achievement, highlighting the importance of a positive mindset (AR1, 0.997), monitoring achievements (AR5, 0.996), and a well-thought-out plan (AR2, 0.981) as critical for success. It also revealed that academic achievement and test anxiety significantly impact performance, with visible signs of nervousness (AT1, 0.146) and exam-related nervousness (AT7, 0.126) being notable factors. Using 1000 epochs, the MLP model achieved optimal accuracy, providing insights into distinct patterns in academic achievement and test anxiety across student groups. These findings can guide educators and policymakers in designing targeted interventions to improve academic outcomes. However, limitations such as a small sample size (264 participants), geographic restrictions, reliance on self-reported data, and a narrow focus on specific variables like self-efficacy and test anxiety may affect generalizability. Future research should expand sample diversity, incorporate additional variables, and explore practical interventions to enhance the understanding of academic achievement. A prediction model was also developed to forecast and analyze future conditions, offering a foundation for further exploration.

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