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Minimizing the Performance Gap: A Neural-Network-Inspired Error-Correction Model for Improving Student Achievement in Somali Higher Education

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Abstract
Artificial neural networks improve their performance by repeatedly measuring the gap between what they produce and what is expected, then adjusting themselves to shrink that gap. This paper proposes that the same principle can be applied deliberately, and formally, to classroom teaching in Somali higher education. We define a simple performance-error formula for students, Error = Actual Marks − Desired Marks, and use it as the basis of a semester-by-semester feedback loop modeled on the forward pass, error computation, and backpropagation steps of a neural network. Rather than a metaphor alone, the paper sets out a concrete, low-cost procedure a lecturer can use each semester: set a desired target per student or course, measure the actual result, compute the error, prioritize interventions by the size and direction of the error, and re-measure in the following semester. We discuss how this model can be implemented with the limited infrastructure typical of many Somali universities, its expected benefits for both students and lecturers, and the practical limitations that must be managed. The paper is intended as a preview of a fuller empirical study to be carried out across upcoming semesters.

Keywords: Neural-Network-Inspired Error-Correction Model, Students, Performance Gap, Somali Higher Education

1. Introduction

A significant obstacle in Somali higher education is the persistent discrepancy between the learning outcomes students are expected to attain and their actual performance by the semester's end. This gap is often recognized informally by lecturers through indicators such as failing grades, substandard exam responses, and recurring errors in assignments. However, these observations tend to remain anecdotal and lack systematic quantification, which limits their utility in informing targeted pedagogical adjustments for subsequent semesters. Without a structured approach to measuring and analyzing this performance gap, educators face challenges in identifying specific areas where students struggle and in implementing evidence-based interventions to enhance learning outcomes [1].

To address this issue, the paper suggests adopting a concept from artificial neural networks, where learning is optimized by explicitly measuring the error between the actual output and the desired output and feeding this error back into the system to guide improvement. Translating this idea to an educational context implies that student performance data should be systematically collected, quantified, and analyzed to identify precise gaps between intended learning objectives and achieved results. This explicit feedback mechanism can then inform curriculum design, teaching methods, and assessment strategies, enabling more focused and effective interventions that accelerate student learning and close the achievement gap more efficiently over time [2].

Learning in a neural network involves an iterative process where the network's output is continuously compared against a target or desired output. This comparison generates an error signal that quantifies the discrepancy between actual and expected results. The network then uses this error to adjust its internal parameters—such as weights and biases—through optimization algorithms like backpropagation, aiming to minimize the error in subsequent iterations. This cycle of prediction, error calculation, and parameter updating enables the network to improve its performance progressively, refining its ability to make accurate predictions or classifications [3].

Translating this concept to an educational setting, a similar feedback loop can be established between a student's performance and instructional strategies. Here, the student's actual marks serve as the network's output, while the marks realistically desired by educators or the student represent the target output. By comparing these two, an error is identified, highlighting the gap between current achievement and learning goals. This error then informs adjustments in teaching methods, study plans, or resource allocation to better support the student's learning. Over time, by iteratively refining these strategies based on performance feedback, educators can help students close the gap, enhancing learning outcomes. The paper elaborates on this analogy by proposing a structured model that lecturers can directly implement to systematically apply this error-driven adjustment process in their classrooms [4].

2. Background: Error Correction in Neural Networks

The supervised error correction mechanism in neural network training fundamentally relies on an iterative process of prediction, evaluation, and adjustment. Initially, the network receives an input and processes it through its layers during the forward pass, generating an output prediction. This prediction is then quantitatively compared to the actual target value, resulting in an error signal that measures the discrepancy between the predicted and desired outputs. This error is crucial as it guides the learning process by indicating how far off the model's prediction is and in which direction the model's parameters need to be adjusted [5].

Following the forward pass, the error is propagated backward through the network using backpropagation, a method that efficiently computes the gradient of the error with respect to each weight in the network. These gradients inform the update of the network's weights, typically via gradient descent or a variant, moving the weights in a direction that minimizes the error. This cycle of forward and backward passes is repeated over many iterations, called epochs, allowing the network to gradually improve its accuracy. The learning rate parameter controls the magnitude of weight updates, balancing the speed and stability of convergence; too high a learning rate can cause divergence, while too low can slow training significantly. Overall, this supervised learning framework enables neural networks to model complex patterns by continuously refining their internal parameters based on the error feedback [6]. This logic can be formalized for classroom use directly, as in Eq. (1):

$$\textit{Error (E)} = \textit{Actual Marks (A)} - \textit{Desired Marks (D)} \quad (1)$$

When a student's desired mark is 100 but the actual mark achieved is 90, the resulting error of −10 quantifies the shortfall from the target. This negative error not only signals underperformance but also provides a measurable indication of how much improvement is needed. The magnitude of the error reflects the distance from the goal, while the negative sign highlights that the performance is below expectations. Together, these aspects allow educators or systems to tailor interventions appropriately, deciding both the intensity and type of support required to help the student improve.

The concept of error-driven learning in neural networks serves as a valuable analogy for educational progress. In neural networks, the system iteratively adjusts its parameters to minimize the error between predicted and desired outputs. Similarly, in education, the goal is to reduce the gap between a student's actual performance and their target mark over time. This iterative process emphasizes continual refinement, where each cycle of assessment and feedback helps to bring the student's achievements closer to their goals [7].

In the educational context, this approach translates into monitoring student performance regularly and using the observed errors to inform teaching strategies. By identifying the magnitude and direction of the performance gap, educators can tailor their interventions more effectively. This dynamic adjustment ensures that support is neither excessive nor insufficient, but precisely calibrated to the student's current needs, thereby optimizing the learning experience and fostering steady improvement [8].

Moreover, this continuous feedback loop allows for the systematic alignment of teaching methods with student progress. As errors decrease semester by semester, instructional approaches can be refined to address emerging challenges and reinforce strengths. This adaptive pedagogy not only enhances learning outcomes but also motivates students by providing clear, measurable indicators of their advancement toward their academic targets [9].

3. Mapping the Neural Network Model to the Classroom

Table 1 sets out the direct correspondence between neural network training concepts and their proposed classroom equivalents. This mapping is what turns the error formula from a simple observation into a repeatable, semester-by-semester improvement cycle.

Table 1: Mapping of Neural Network Concepts to Classroom Equivalents

NN Concept	Classroom Equivalent
Target output (D)	The desired/target mark the lecturer and student agree on for a course (e.g., 100, or a pass threshold).
Actual output (A)	The mark the student actually obtains in a quiz, midterm, or final exam.
Error (E = A − D)	The performance gap for that student in that assessment; a large negative error signals a student in need of support.
Backpropagation	Feeding the error back to the lecturer, advisor, and student so that teaching and study strategies for the next unit/semester are adjusted.
Learning rate	The intensity and pacing of the intervention — how much tutoring, revision, or curriculum adjustment is applied per unit of error.

Epoch	One academic semester; each semester is a fresh pass through the same feedback cycle, with the model (teaching approach) updated from the previous epoch's errors.
Convergence	The student's error trending toward zero over successive semesters, i.e., actual marks approaching the desired marks.

4. Proposed Implementation Framework

4.1 Steps of the Implementation Framework

Step 1 — Set the Desired Marks (the Target)
At the start of a course, the lecturer and, where practical, the student agree on a realistic desired mark — this may be a fixed institutional target (e.g., 100, or the pass mark of 50), or an individualized target based on the student's prior performance and stated goals. This target plays the role of the desired output (D) in the model.

Step 2 — Measure Actual Performance
Actual marks (A) are collected from existing assessment instruments already used in Somali universities: quizzes, assignments, midterm exams, and final exams. No new measurement infrastructure is required; the model reuses data lecturers already generate.

Step 3 — Compute and Diagnose the Error
For each student and each assessment, the lecturer computes $E = A - D$. Students can then be grouped by the size of their error: those with error near zero are on track; those with moderate negative error need targeted revision; those with large negative error need urgent, structured support. This turns a spreadsheet of raw marks into a prioritized list of who needs help and how urgently.

Step 4 — Corrective Intervention (the "Learning Rate")
The size of the error determines the intensity of the intervention, in the same way the learning rate scales a weight update in a neural network. Practical interventions available in a typical Somali university setting include:

- Extra tutorial or revision sessions for students with large negative error.
- Peer-assisted learning, pairing high-performing students with those showing large gaps.
- Adjusting pacing or re-teaching a topic when many students show error on the same content area.
- Short, frequent formative quizzes so error is measured (and corrected) before it accumulates into a large final-exam gap.
- Individual academic advising sessions for students with persistent negative error across multiple courses.

Step 5 — Iterate Across Semesters (the "Epoch")
Each semester functions as one epoch. At the end of the semester, the error is recomputed, and the pattern of errors from the current semester informs the interventions planned for the next one. Over several semesters, a student's error should trend toward zero — the classroom equivalent of a converging neural network. Tracking this trend also gives the lecturer and the faculty a simple, quantifiable way to demonstrate whether an intervention is working [10].

4.2 Illustrative Example

Consider three students in the same course, all sharing a desired mark of 100. Table 2 shows how the error formula immediately separates students who need no intervention from those who need urgent support — a distinction that a raw mark alone shows, but that the explicit error framing makes actionable and easy to rank across an entire class.

Table 2: Illustrative Application of the Error Formula to Three Students

Student	**Desired (D)**	**Actual (A)**	**Error (E = A − D)**	**Intervention Priority**
Student 1	100	90	**−10**	Low
Student 2	100	55	**−45**	High
Student 3	100	100	**0**	None (maintain)

This indicates that Student 2, who has a large negative error of −45, needs urgent or specialized support because their performance is far below the target. Student 3, who has zero error, is meeting the target exactly and requires only regular support, such as more challenging or advanced material, rather than additional help to catch up. In this way, interventions are prioritized according to how far each student is from their target.

4.3 Expected Benefits

- Gives lecturers a simple, low-cost, quantifiable diagnostic tool that requires no new software or hardware.
- Shifts attention from an end-of-semester grade alone to a trackable gap that can be acted on before the next exam.
- Makes it possible to compare intervention effectiveness across semesters using the same metric (mean error, or proportion of students with error above a threshold).
- Encourages goal-setting conversations between lecturer and student, since a 'desired mark' must be made explicit rather than left implicit.
- Provides a natural bridge to more advanced, data-driven interventions (e.g., early-warning systems) as Somali universities' data infrastructure matures.

4.4 Challenges and Limitations in the Somali Context

- Large class sizes can make individualized target-setting and error tracking time-consuming without basic spreadsheet or LMS support.
- Inconsistent or incomplete assessment records across semesters can make it hard to track a student's error trend over time.
- Desired marks must be set realistically; an unrealistic universal target (e.g., 100 for every student) risks discouraging students whose error will rarely reach zero for reasons unrelated to effort.
- The model diagnoses the size of a gap but does not by itself explain its cause; it must be paired with lecturer judgment about why a given student's error is large.
- Sustained use across semesters requires institutional buy-in so that error data is retained and reviewed consistently rather than informally by individual lecturers.

5. Conclusion and Future Work

This paper has outlined how a simple, neural-network-style error formula, Error = Actual − Desired, can be turned into a practical, semester-by-semester feedback loop for improving student performance in Somali universities. The approach requires no new technology, only a disciplined habit of setting targets, measuring gaps, prioritizing intervention by the size of the gap, and re-measuring the following semester. As a next step, the author intends to pilot this framework across one or more courses over upcoming semesters, tracking the mean class error and its trend as a simple indicator of whether the intervention cycle is working, before extending the model with lightweight digital tools for tracking error across cohorts and semesters.

Conflict of Interest

The author confirms no conflict of interest.

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