# A Deep Learning-Based Blended Model for Enhancing English Proficiency in Sports Students through Athlete Training Modules

**Feng Hongli[1]*, Goh Chin Shuang[2]**

**Abstract**
Sports students often face challenges in language proficiency, which can impede their overall academic and professional development. Traditional language learning methods may not fully engage them, particularly in environments primarily focused on physical training. Combining athletic training with language acquisition offers the potential to enhance both cognitive and linguistic abilities. This study aims to design and evaluate a deep learning-based blended model to improve English proficiency among sports students through specialised athlete training modules. A deep learning model, combining Binary Chimp-Assisted Residual Network (BC-RN), was developed to track and analyse student progress in both athletic training and language acquisition. The model was implemented via interactive training modules that integrated language-focused exercises alongside sports-specific drills. Data were collected from a cohort of 100 sports students, with pre- and post-assessments measuring improvements in English language proficiency (vocabulary, listening, and speaking) and physical performance (strength, agility), and pre-processed using Z-score normalisation. The findings revealed that BC-RN outperformed other existing models, achieving an accuracy of 85.61%. Furthermore, the AUC increased from 0.92 to 0.95, while the RMSE decreased from 0.25 to 0.15. These results demonstrate that BC-RN is the most effective model for predicting blended teaching performance, offering more accurate and reliable predictions. Student engagement and feedback were positive, indicating that the dual approach enhanced learning in both domains. Future research should explore the scalability of the model to other disciplines and incorporate real-time adaptive learning features to further personalise the learning experience.
**Keywords:** Deep Learning, Blended Learning Model, English Proficiency, Sports Students, Binary Chimp-Assisted Residual Network (BC-RN), Speaking Fluency.

## Introduction

In today's world, sports are highly popular, and athletes can greatly benefit from proficiency in a foreign language, particularly English, for their professional careers. Learning English is essential for future experts in physical culture and sports, as it enables them to discuss various events, games, and professional training, which are crucial for both their academic and professional development. Consequently, sports professionals must meet higher standards in their language training. However, the issue is exacerbated by the fact that many sports students continue to exhibit low levels of foreign language proficiency (Djalilova et al., 2024). The practice of teaching English at the university level has shown that most students struggle to communicate verbally in English, and traditional methods of teaching English to sports students have not been entirely successful. It is believed that the primary issue lies in the lack of emphasis on the development and cultivation of communication skills. Often, student athletes' expertise is limited to reading and translating short, simplified texts, which are far removed from authentic "living" sports terminology. Language proficiency typically follows a linear trajectory based on the subject matter of the study (Vorobel et al., 2023).

Learning English should encompass more than just acquiring language skills such as phonology, pragmatics, vocabulary, and critical thinking. A multi-layered approach is employed in foreign language acquisition, where teachers plan and model the learning process progressively. The curriculum stipulates that during the first year of university study, both general and specialised sports vocabulary is introduced in a structured manner (Sato et al., 2022). During this period, students strengthen their broader English vocabulary, laying the foundation for mastering more specific terms. In addition to vocabulary, students are also exposed to general sports terminology, which is taught through real-world training scenarios and simulations of specific sports (Hut et al., 2023; Zhang, 2022). However, textbooks used in educational institutions, which are designed to teach all four language skills and adhere to traditional methods, often fail to develop the communication skills needed for professional sports. As a result, instructors must independently create language scenarios for professional-oriented communication, supplementing textbook content and instructional exercise manuals (Ali Mansoor et al., 2023).

While top British scientists produce a substantial amount of reliable content in fields such as economics, law, and medicine, sports guides become valuable in the absence of similar resources (Aizawa et al., 2023). The textbooks currently available rarely include

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materials with a strong focus on sports or innovative language exercises designed to develop skills in professional-oriented and role-playing games. Consequently, the learning process is significantly influenced by the integration of prior knowledge and real-world scenarios, which in turn plays a crucial role in enhancing the student's motivation (Ceneciro et al., 2023; Mamajanova, 2022).

Physical education professionals often perceive little relevance for foreign languages, which can demotivate students from learning them. Many students who study English do not view it as essential for their future careers and believe it "will carry." As a result, instructors need to take decisive action beyond simply explaining the subject. They should actively encourage students and emphasise the importance of learning a second language for their professional development, particularly in the role of a psychologist. However, interest in learning a foreign language tends to diminish as students' progress through educational institutions. Primary school students, in contrast, are generally more motivated to learn and absorb new information (Yang, Chen, et al., 2022). This decline in motivation is influenced by factors such as the novelty of the subject, teaching methodologies, task assignments, evaluation systems, and lesson designs, which differ from traditional classroom instruction. As interest wanes, learning effectiveness decreases. This is attributed to the foreign language subjects disconnect from students' actual needs, the complexity of lexical and grammatical content, and a lack of proficiency in tackling language-related tasks. Despite these challenges, students remain significantly interested in the content, especially when it is professionally oriented. Although the curriculum requires students to master all four language skills, the limited class time often hinders this goal. Consequently, the focus of instruction must be adjusted to better align with students' needs and the practical demands of their future careers (Hu et al., 2022).

This study proposes the development of a hybrid model based on the BC-RN to enhance the English language skills of sports students through the integration of athlete training modules. The BC-RN model aims to optimise athletic performance while simultaneously improving speaking, listening, and vocabulary skills by combining language acquisition with physical training.

**Contributions of the Study**

1. By offering a more dependable instrument for evaluating and improving instructional tactics in blended learning settings, the study suggested approach advances the field of educational technology.
2. The study presents BC-RN, a unique deep learning-based model for more accurate prediction of blended teaching success.
3. Pre-processing data using Z-score normalization improves model performance by normalizing input features for improved learning and prediction.

The investigation is organised as follows: Part 2 presents the literature review, Part 3 outlines the methodology, Part 4 discusses the results and analysis, and Part 5 provides examples to support the conclusion.

## Literature Review

To regulate students in physical education, Zhang (2022) proposed an intellectual student progress estimation system that employs deep learning (DL). The system assesses the level of learning, retention, and achievements of students, while also recommending enhancements and remedial actions. It highlights the benefits, applications, and limitations of using IoT devices and DL techniques to develop learning analytics systems in real-world educational settings. Finally, a feature-by-feature comparison was conducted between the proposed methods and traditional teaching-learning approaches, focusing on output criteria such as comprehension, concentration, retention, and learner achievement.

Li et al. (2024) explored the development of an advanced video resource platform that transforms the learning process through the integration of multimedia technologies and micro-videos. The platform utilised a variety of micro-videos and multimedia networks to form its foundation, incorporating elements of animation, video, and real-time chat to create an engaging learning experience. Additionally, the platform applied principles of expert teaching, including the use of information assessment to monitor student learning and adjust teaching methods in response to individual progress. The learning and teaching experience outlined by Gómez-Ortiz et al. (2023) employs a project-based methodology using Instagram accounts to enhance technical vocabulary in the classroom. Participants were divided into 16 self-organised groups, each tasked with creating a fitness initiative via Instagram profiles. After the activity, students completed an ad hoc questionnaire regarding their perceptions of using Instagram as a tool to learn specific sports science terminology. The students expressed strong support for using Instagram to expand their technical vocabulary.

Ongoro et al. (2023) provide a comprehensive review of the literature on applying game-based learning technologies to teach English as a foreign language. They argue that digital game-based learning (DGBL) can enhance language acquisition and learner motivation. Their review presents a four-part classification schema for DGBL in foreign language learning, covering structural and functional characteristics, language load, educational and developmental components, and feedback. Du et al. (2022) explored the use of DL-based Massive Open Online Courses (MOOCs) for teaching English grammar to college students, gathering data through a questionnaire. The results indicated that students were dissatisfied and uninterested in acquiring language skills or practising spoken English. Despite this, the study highlighted that DL-based learning environments, combined with high-quality online resources, offer interactive features that enable virtual interaction between students and instructors.

According to Gao et al. (2024), modern teaching models provide colleges and institutions with a useful tool for evaluating College English Teaching (CET), addressing the complex demands of collaborative research and incorporating diverse approaches required by students. To overcome the challenges of traditional Teaching Evaluation Methods (TEM), the paper introduces a novel machine learning model. However, the research findings suggest that the TEM model outperformed the other models in evaluating English teaching. Recognising students' learning behaviour is essential for understanding changes in their psychological traits, correcting negative learning behaviours, and improving learning efficiency. Lu et al. (2022) proposed an automatic technique based on the ADL model to recognise student behaviour in an English classroom. The DL model was primarily utilised to process video data from these classrooms.

The amount of time and frequency English majors dedicated to learning the language significantly affected their classroom engagement. Traditional emotion recognition techniques for learners had several drawbacks, including low identification rates, complex algorithms, poor robustness, and the loss of crucial facial expression data. To address these issues, Zhang, Sengan, et al. (2022) proposed a CNN-based learner emotion recognition technique consisting of three convolution layers, three pooling layers, and one fully connected layer. In Chen et al. (2022), a dynamic learning system was developed to enhance students' English-speaking fluency. A quasi-experiment was conducted to evaluate the system's effectiveness in improving speech learning outcomes. The experimental group used the DA-SR approach, while the control group followed the Corrective Feedback-based Speech Recognition (CF-SR) approach.

Liu et al. (2022) proposed an e-learning system model for content customisation based on learners' emotions. The system utilised a portable electroencephalogram to monitor students' brain waves in real time and analyse their emotions using the K-nearest neighbours (KNN) algorithm under supervised machine learning. Additionally, using reinforcement learning, the system suggested relevant materials to support students' positive emotions based on emotional assessments. Gultom et al. (2022) explored the role of literature in enhancing the speaking skills of EFL learners, highlighting graphic books as valuable resources for providing students with engaging, creative, and aesthetic experiences. A quantitative research methodology, including online class observation and survey data, was used to assess the impact of literature on communication skills, speaking proficiency, and speech fluency. Al-Alawi et al. (2023) examined the factors negatively impacting the academic performance of college students on probation using supervised machine learning algorithms. Ensemble methods and the Information Gain (Info Gain) algorithm were employed to identify the most effective features and evaluate the accuracy of algorithms such as logit boost, vote, and bagging.

Zhang, Zhou, et al. (2022) assessed the impact of a blended teaching method on nursing students' competency and self-directed learning levels in an obstetrics and gynaecology nursing course. The study compared the self-directed learning and competency scores of a control group receiving traditional instruction with an experimental group using blended learning. Statistical analysis was employed to evaluate the differences between the two groups.

## Methodology

For this investigation, data from 100 students with blended teaching test results (BTTR) were collected through pre- and post-tests. The data were pre-processed using Z-score normalization, and the normalized data were then analysed for blended teaching performance using the BC-RN model. Figure 1 illustrates the methodology flow.

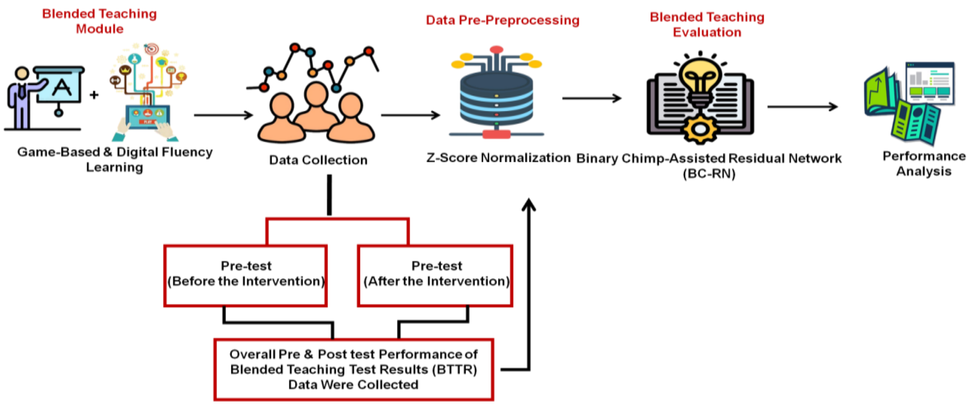


***Figure 1:*** Method Flow.

**Blended Teaching Module**

This study employs a blended teaching module that integrates game-based learning and digital fluency strategies, using a sports-focused Blended Teaching (BT) method. The module's primary objective is to simultaneously improve students' physical therapy and English language skills. By combining language-focused drills with game-like elements and sports-themed activities, the module enables students to practice speaking, listening, and using appropriate vocabulary, among other skills. The module also incorporates digital fluency tools with feedback and adaptive assistance features. Overall, the blended module aims to enhance the development of both language and sports skills through innovative and engaging, fun-based activities.

**Data Collection**

For this study, 100 students were selected to analyse the effectiveness of the blended module in enhancing English proficiency among sports students through specialised athlete training modules. The students' blended teaching performance was assessed based on their overall performance in the pre-test and post-test. The pre-test was conducted before the implementation of blended teaching, while the post-test was administered after the implementation of the BT method. Two sets of performance data, known as BTTR, were used in this investigation to evaluate the outcomes.

**Table 1**

*Data Collection for Blended Teaching Intervention*

| Stage | Metrics Assessed | Description | Data Collected |
|---|---|---|---|
| Pre-Test | English Proficiency (Vocabulary, Listening, Speaking) | Evaluates the Linguistic Proficiency of the Children Before the Intervention. | Pre-Test and Post-Test Performances of BTTR Data were Collected. |
| | Physical Performance (Strength, Stability) | Evaluates the Physical Prowess of the Pupils Before the Intervention. | |
| Post-Test | Sports-Integrated Language Learning (Game-Based & Digital Fluency) | The Program includes Both Sports-Specific Activities and English Language Skills. | |

**Data Pre-Processing using Z-Score Normalization**

Z-standardization of the data is performed as part of the pre-processing phase to normalise the given dataset of BTTR features, ensuring that the calculated mean equals zero and the standard deviation equals one. This process eliminates biases that may arise from the frequency of certain language usage, physical performance indicators such as vocabulary scores or agility times, and other potential discrepancies. By standardising the data, the model becomes more stable and accurate when analysed with varying data inputs. Furthermore, it prevents extreme values, such as maximum and minimum values, or out-of-range data from skewing the results, thus improving the overall accuracy. Normalisation is achieved using the formulas in Equations (1-3). Figure 2 illustrates the process of normalisation.

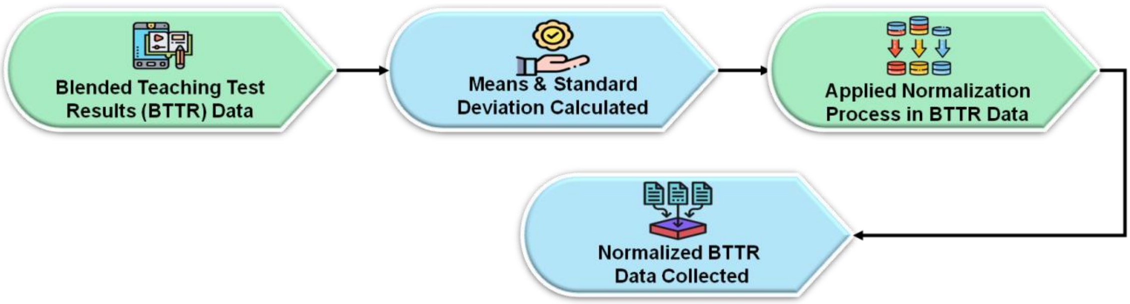


***Figure 2:*** Normalization Process.

$$v_i{}' = \frac{v_i - E}{std\,(E)} \tag{1}$$

Where $v_i$ is the Z-score value normalized to one, and $v_i$ is the value of the $i^{\text{th}}$ column's row $E$.

$$std(F) = \sqrt{\frac{1}{(m-1)}\sum_{j=1}^{m}(u_j - \bar{F}\,)^2} \tag{2}$$

$$\bar{F} = \frac{1}{n}\sum_{j=1}^{m} u_j \tag{3}$$

Consequently, the Z-score approach is used to determine the normalized values for each row. If the standard deviation of a row is 0, meaning all values are identical, then all values for that row are set to zero. After applying Z-score normalization, the BTTR data collected will have standardized values for both language and physical performance measures, ensuring consistency and comparability across the dataset.

**Predicting the Blended Teaching Performance using Binary Chimp-Assisted Residual Network (BC-RN)**

After the normalisation of the BTTR data, the BC-RN model is designed to enhance the precision and effectiveness of forecasting improvements in both linguistic competency and physical performance. The model leverages the BC-RN's ability to manage residual learning, allowing it to efficiently uncover intricate patterns in the normalized data. As a result, sports students benefit from more accurate tracking of their progress in both language acquisition and athletic training. Additionally, by minimising training errors, the BC-RN ensures more stable and reliable predictions, leading to consistent performance improvements.

**Residual Network (RN)**

After normalising the BTTR data, the RN is employed to enhance model performance by focusing on learning the residuals, or errors, between the expected and actual results. By facilitating deeper learning of complex elements in the normalised data, RN improves prediction accuracy for both linguistic and physical performance indicators. It also aids in better convergence during training by addressing the vanishing gradient issue. Consequently, predictions of students' progress in both linguistic and physical training become more accurate and reliable. Recent relevant CNN results have incorporated residual designs. Figure 3 illustrates the standard residual block. A transformation of a residual block given a generic input W along with a mapping E is presented in Equation (4).

$$W' = E(W) + W \quad (4)$$

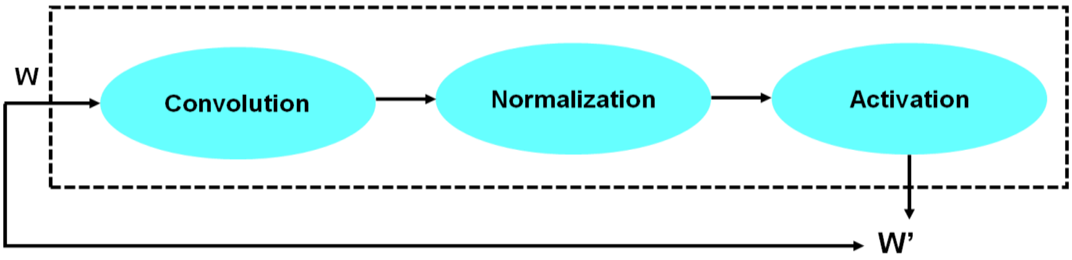


***Figure 3:*** Residual Block.

RN variations have been proposed and applied in various contexts. For both linear and nonlinear $E(W)$ scenarios, guarantees were provided, and a series of near-identical adjustments involving residual blocks were extensively studied. In this case, a simple attention mechanism, commonly referred to as intra- or self-attention, is employed. Let $z_{1,S}$ represent a set of vectors that correspond to a neural network's outputs for a given input. Equation (5) states that a set of scalar $sa_{1,S}$ is produced by applying a linear transformation $X$, which is shared across all time-stepss, to each $z_s$.

$$b_s = \tanh(X_{z_s}) \quad (5)$$

Equation (6) presents the softmax operator, which yields a place of normalized weights that add up to 1. Equation (7) provides the attention layer output.

$$x_s = \frac{f^{b_s}}{\sum_{s=1}^{S} f^{b_s}} \quad (6)$$

$$z = \sum_{s=1}^{S} x_s z_s \quad (7)$$

By enabling deeper learning of complex features in the normalised data, RN enhances prediction accuracy for both linguistic and physical performance indicators. It also ensures better convergence during training by helping mitigate the vanishing gradient problem.

**Binary Chimp optimization (BChO)**

To optimise the network's hyperparameters and enhance model performance, BChO is applied to the BTTR data following the RN procedure. BChO effectively searches for optimal values for parameters such as learning rate, layer weights, and activation functions, thereby improving prediction accuracy. It ensures the model minimises errors while achieving the ideal balance between overfitting and underfitting. As a result, the optimisation procedure leads to better outcomes in both language and physical performance evaluations, as well as improved generalisation. Figure 4 illustrates the BChO process.

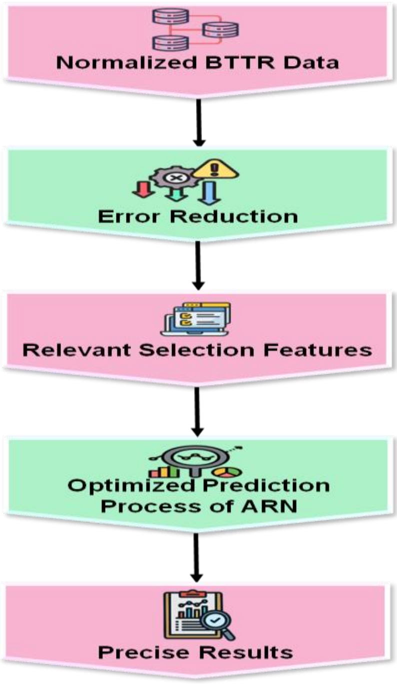


***Figure 4:*** Optimization Process.

Equation (8) defines the crossover operator used to update the chimpanzee's position in the BChO algorithm.

$$W(s+1) = Crossover(Z_1, Z_2, Z_3, Z_4) \quad (8)$$

Where the binary vectors $Z_1, Z_2, Z_3, and Z_4$ show the movements of the first four chimpanzees. The crossover operation between solutions is called crossover $(Z_1, Z_2, Z_3, Z_4)$. Equation (9) can be used to calculate the binary vectors $Z_1, Z_2, Z_3, and Z_4$, which are impacted by the movement of the first four champs, respectively.

$$Z_1^c = \begin{cases} 1, if\ (W_B^c + astep_B^c) \geq 1 \\ 0, Otherwise \end{cases} \quad (9)$$

If $W_B^c$ is the attacker's position vector, the search space has dimensions, and the binary step, denoted by $astep_B^c$, is determined by Equation (10).

$$astep_B^c = \begin{cases} 1, if\ dstep_B^c \geq q_3 \\ 0, Otherwise \end{cases} \quad (10)$$

Equations (11 & 12) define $dstep_B^c$ as a continuous-valued step size and $q_3$ as a random vector with values between 0 and 1.

$$dstep_B^c = \frac{1}{1+exp(-10(B_1^c C_B^c - 0.5))} \quad (11)$$

$$Z_2^c = \begin{cases} 1, if\ (W_A^c + astep_B^c \geq 1 \\ 0, Otherwise \end{cases} \quad (12)$$

Whereas the search space has dimension $c$ and $W_A^c$ is the barrier's position vector, Equation (13) computes the binary step.

$$astep_B^c = \begin{cases} 1, if\ dstep_B^c \geq q_4 \\ 0, Otherwise \end{cases} \quad (13)$$

Equations (14 & 15) define $dstep_B^c$ as a continuous-valued step size, and $q_4$ is a randomized variable with values between 0 and 1.

$$dstep_B^c = \frac{1}{1+exp(-10(B_2^c C_A^c - 0.5))} \quad (14)$$

$$Z_3^c = \begin{cases} 1, iif\ (W_D^c + astep_B^c) \geq 1 \\ 0, otherwise \end{cases} \quad (15)$$

Where the search space has dimension $c$, the chaser's position vector is $W_D^c$, and the binary step, $astep_B^c$, is determined by Equation (16.

$$astep_d^c = \begin{cases} 1, if\ dstep_D^c \geq q_5 \\ 0, otherwise \end{cases} \quad (17)$$

Equations (18 & 19) define the continuous-valued step size as $dstep_d^c$, where $q_5$ is a randomized vector with elements between 0 and 1.

$$dstep_d^c = \frac{1}{1+exp(-10(B_3^c C_D^c - 0.5))} \quad (18)$$

$$Z_4^c = \begin{cases} 1, if\ (W_C^c + astep_D^c) \geq 1 \\ 0, otherwise \end{cases} \quad (19)$$

The dimension of the search space is $c$ and $astep_d^c$ is, the binary step that is determined by Equation (20) as follows, and $W_C^c$ is the driver's position vector.

$$astep_d^c = \begin{cases} 1, if\ dstep_D^c \geq q_6 \\ 0, otherwise \end{cases} \quad (20)$$

Where Equation (21) defines $dstep_C^c$ as as a continuous-valued step size and $q_6$ is a random vector with values between 0 and 1.

$$dstep_C^c = \frac{1}{1+exp(-10(B_4^c C_D^c - 0.5))} \quad (21)$$

To enhance prediction accuracy, BChO efficiently searches for the optimal values of parameters such as learning rate, layer weights, and activation functions. It ensures the model strikes the ideal balance between overfitting and underfitting while minimizing errors. This optimisation process improves generalisation and leads to better performance in both language and physical performance assessments. Algorithm 1 illustrates the flow of the BC-RN model.

**Algorithm 1: Binary Chimp-Assisted Residual Network (BC-RN)**

$\boldsymbol{Step1}: Initializethepopulationofbinarychimpanzeeswithrandomvaluesforhyperparameters.$

$\boldsymbol{Step2}: NormalizetheBTTRdata.$

$\boldsymbol{Step3}: Foreachchimpanzee, applytheBinaryChimpOptimization\ (BChO)\ processtoupdatehyperparameters.$

$\boldsymbol{Step4}: Defineresidualnetwork\ (RN)\ structurewithresidualblockstofocusonerrorcorrection.$

$\boldsymbol{Step5}: Applyattentionmechanism\ (Eq.5-7)\ toenhancelearningofkeyfeatures.$

$\boldsymbol{Step6}: ForwardpassthroughtheBC-RNmodeltocomputepredictionsforlinguisticandphysicalperformance.$

$\boldsymbol{Step7}: Calculatethelossbetweenpredictedandactualoutcomes.$

$\boldsymbol{Step8}: Backpropagateerrorusingresiduallearning\ (Eq.4)\ toupdatemodelweights.$

$\boldsymbol{Step9}: Repeattheoptimizationprocess\ (BChO)\ torefinehyperparametersusingcrossover\ (Eq.8-12).$

$\boldsymbol{Step10}: Continuetraininguntilmodelconvergenceormaxiterations, thenevaluateperformance.$

## Results and Discussion

This study proposes the development of a hybrid model based on BC-RN to enhance the English language proficiency of sports students through the incorporation of athlete training modules. The BC-RN model aims to integrate language and physical training to improve speaking, listening, and vocabulary skills while simultaneously optimising athletic performance. Python 3.11 was utilised extensively in the investigation, which was conducted on Windows 10 desktops equipped with Intel Core i8 processors and 32GB SSDs. Figure 5 of the BC-RN model demonstrates a reduction in error as the number of training iterations increases. Initially, the fitting error is relatively high, but it decreases as the model iterates and learns from the data, illustrating the successful acquisition of knowledge and the subsequent improvement in prediction accuracy. Specifically, for predictions related to blended teaching performance, the graph should exhibit a consistent decline in fitting error, indicating the network's ability to identify complex patterns within the data. Over time, if the graph levels off, it suggests that BC-RN is operating at optimal efficiency. However, a rise in fitting error after numerous iterations may signal overfitting, indicating the need for further refinement or adjustments to the model.

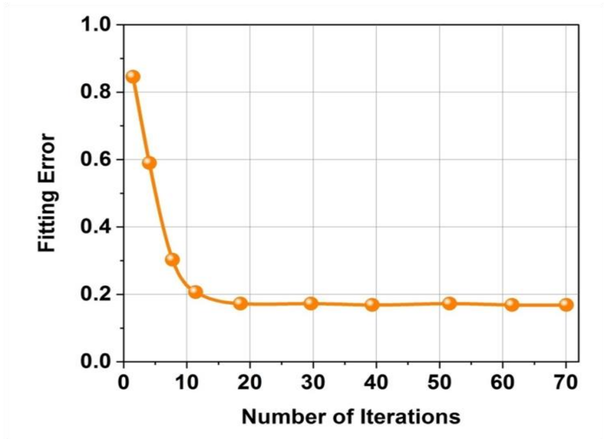


***Figure 5:*** BC-RN Output Graph.

**Comparative Analysis**

This study compares the proposed BC-RN technique with various existing methods, including Deep Belief Network (DBN) (Yang, Zhang, et al., 2022), Repeated Incremental Pruning to Produce Error Reduction (JRip), Decision Tree (J48), Partial Decision Tree (PART), and Randomised Decision Tree (RandomTree) (Chango Sailema, 2021), to assess blended teaching performance. Performance metrics used include accuracy, R, RMSE, and AUC. The effectiveness of the BC-RN model in forecasting blended teaching performance is demonstrated in Table 2 and Figure 6, where the R-values (correlation coefficients) of the proposed method are compared with existing approaches. For Dataset D1, BC-RN achieves an R-value of 0.96, outperforming DBN (0.92). In D6, BC-RN delivers an R-value of 0.98, surpassing the current method's 0.95. For D8, BC-RN's R-value of 0.91 exceeds the current approach's 0.86, and for D3, BC-RN achieves 0.97, outperforming the current value of 0.95. These results highlight BC-RN's superior performance in predicting blended learning outcomes, demonstrating the model's increased reliability and making it the best approach for aligning predictions with actual performance.

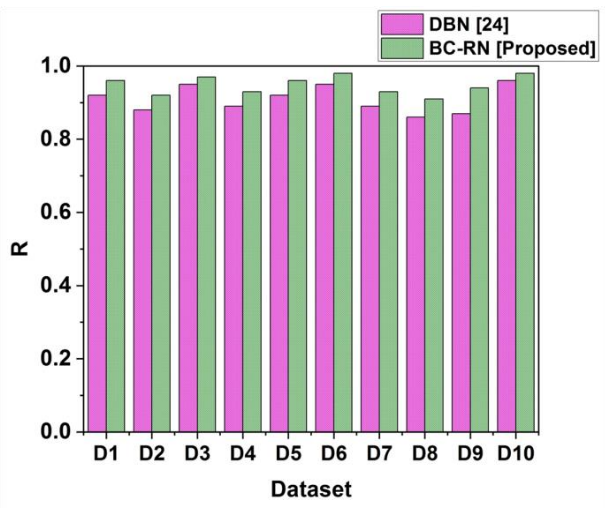


***Figure 6:*** Comparison of Dataset Performance.

**Table 2**

*Overall Dataset Comparison*

| | R Value | |
|---|---|---|
| Dataset | **DBN** | **Proposed** |
| $D_1$ | 0.92 | 0.96 |
| $D_2$ | 0.88 | 0.92 |
| $D_3$ | 0.95 | 0.97 |
| $D_4$ | 0.89 | 0.93 |
| $D_5$ | 0.92 | 0.96 |
| $D_6$ | 0.95 | 0.98 |
| $D_7$ | 0.89 | 0.93 |
| $D_8$ | 0.86 | 0.91 |
| $D_9$ | 0.87 | 0.94 |
| $D_{10}$ | 0.96 | 0.98 |

The efficiency of BC-RN in minimising prediction errors for blended teaching performance is demonstrated in Table 3 and Figure 7, which compare the RMSE values of the proposed model with DBN. In Dataset D1, BC-RN achieves an RMSE of 0.15, significantly lower than DBN's 0.25. In D6, BC-RN reduces the RMSE to 0.09, compared to DBN's 0.17. Similarly, in D7, BC-RN outperforms DBN (0.41) with an RMSE of 0.18. Across all datasets, BC-RN consistently achieves lower RMSE values, highlighting its superior precision and reliability in forecasting blended teaching performance.

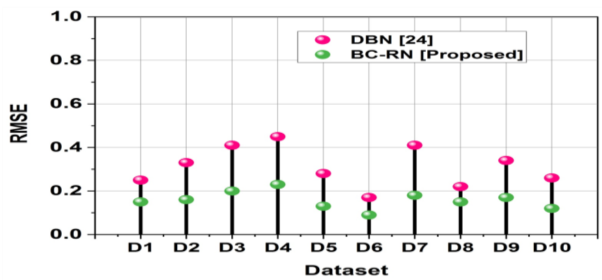


***Figure 7:*** Comparison of RMSE.

**Table 3**

*Overall RMSE Comparison*

| | RMSE | |
|---|---|---|
| **Dataset** | **DBN** | **Proposed** |
| $D_1$ | 0.25 | 0.15 |
| $D_2$ | 0.33 | 0.16 |
| $D_3$ | 0.41 | 0.2 |
| $D_4$ | 0.45 | 0.23 |
| $D_5$ | 0.28 | 0.13 |
| $D_6$ | 0.17 | 0.09 |
| $D_7$ | 0.41 | 0.18 |
| $D_8$ | 0.22 | 0.15 |
| $D_9$ | 0.34 | 0.17 |
| $D_{10}$ | 0.26 | 0.12 |

Figure 8 contrasts the accuracy (%) of various models in forecasting blended learning performance. BC-RN, with an accuracy of 85.61%, outperforms Jrip and J48 (82.45%), PART (80.70%), and RandomTree (77.19%). This highlights BC-RN's superior prediction capacity. The improvement in accuracy demonstrates its ability to identify complex patterns in the data. By employing advanced residual learning, BC-RN ensures higher prediction accuracy and reliability, making it the most effective model for forecasting blended learning outcomes.

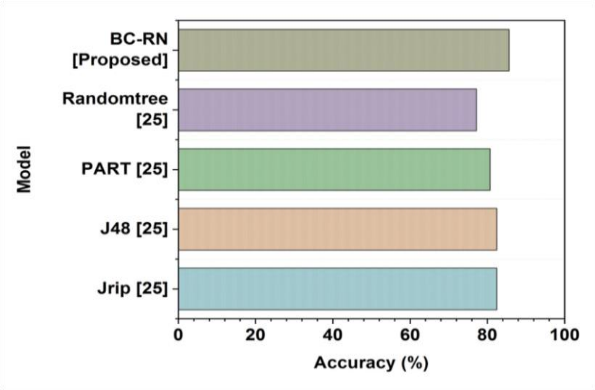


***Figure 8:*** Accuracy Analysis

Figure 9 presents the AUC values of various models for predicting blended learning performance. The BC-RN model, with an AUC of 0.95, outperforms Randomtree (0.83), J48 (0.91), Jrip (0.92), and PART (0.90). This superior AUC value highlights BC-RN's ability to distinguish between different levels of blended teaching performance more effectively than the other models. A higher AUC indicates better model discrimination and enhanced prediction reliability. Based on these results, BC-RN is unequivocally the most effective model for forecasting blended learning outcomes (Figure 9; Table 4). As such, BC-RN demonstrates superior reliability and accuracy in predicting blended teaching performance.

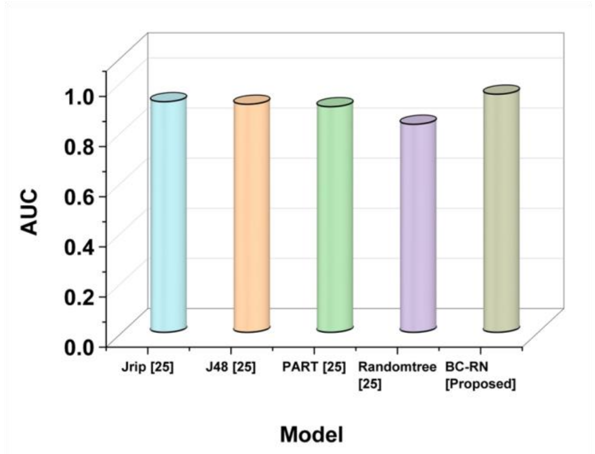


***Figure 9:*** AUC Outcomes.

**Table 4**

*Overall Performance Analysis*

| Model | Accuracy (%) | AUC |
|---|---|---|
| Jrip | 82.45 | 0.92 |
| J48 | 82.45 | 0.91 |
| PART | 80.70 | 0.90 |
| Randomtree | 77.19 | 0.83 |
| BC-RN [Proposed] | 85.61 | 0.95 |

This study proposes the development of a hybrid model based on BC-RN to enhance the English language skills of sports students through the integration of athlete training modules. The BC-RN model aims to maximise athletic performance while improving speaking, listening, and vocabulary skills by combining language and physical training. In contrast, existing models such as Jrip, which employs rule-based learning, may struggle to effectively capture non-linear patterns in the data, limiting its performance (Chango Sailema, 2021). Additionally, Jrip is prone to overfitting when dealing with high-dimensional or noisy datasets. Similarly, the J48 decision tree method can easily overfit when the tree is too deep, limiting its generalisation capabilities. It is also less adept at handling missing values and may fail to capture the intricate interactions necessary for accurate blended learning predictions. The performance of PART, as noted by Chango Sailema (2021), is similarly constrained by its reliance on rule induction to generate simplified models, which may fail to capture subtle patterns in the data. Furthermore, PART may struggle with highly imbalanced datasets, potentially leading to projection imbalances and reduced accuracy.

Chango Sailema (2021) note that the ensemble structure of Randomtree, a random forest version, may be less interpretable compared to other models. This approach may fail to capture key aspects of blended teaching performance and suffers from high computational complexity when dealing with large datasets. To address these limitations, a BC-RN model is proposed, designed to enhance the accuracy of performance prediction for blended learning while overcoming the shortcomings of existing methods. The BC-RN model leverages the advantages of neural networks, enabling it to effectively control overfitting, properly address complex interactions, and promote generalisation. Moreover, it is more accurate for high-dimensional datasets and offers better interpretability than ensemble techniques like Randomtree (Chango Sailema, 2021).

## Conclusion

The study sought to develop and validate BC-RN, a novel model for predicting blended teaching performance, addressing the limitations of traditional models such as Jrip, J48, PART, and Randomtree. The primary objectives of the research were to enhance the model's generalisability for educational applications, reduce errors, and improve predictive effectiveness. Through experimentation on various datasets, the proposed BC-RN model demonstrated superior performance metrics in comparison to existing methods. The results indicated that BC-RN achieved a higher accuracy of 85.61%, outperforming other models—Jrip (82.45%), J48 (82.45%), PART (80.70%), and Randomtree (77.19%). Additionally, the model improved the Area Under the Curve (AUC) from 0.92 to 0.95 and reduced the RMSE from 0.25 to 0.15. These findings suggest that BC-RN is the most effective model for predicting blended teaching performance, offering accurate and reliable predictions. The study further demonstrates that the integration of BC-RN can enrich educational decision-making and provide more insightful recommendations for blended learning environments. However, a limitation of this research is the model's reliance on a specific dataset, which may affect its applicability to other educational contexts. Future research should consider expanding the dataset and incorporating additional variables to improve the generalisability of BC-RN and its applicability across diverse educational settings.

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