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Application of Frbf Network Autonomous Learning Algorithm Based on Intrinsic Motivation in English Network Teaching

Abstract: - An autonomous learning algorithm based on intrinsic motivation represents a cutting-edge approach to network teaching in English education. By harnessing intrinsic motivation, this algorithm empowers learners to autonomously engage with English language materials and activities, driven by their innate curiosity and desire for mastery. Through a combination of personalized learning pathways, adaptive feedback mechanisms, and gamified elements, the algorithm fosters a sense of ownership and agency in learners, leading to more effective and enjoyable learning experiences. Learners are encouraged to explore, experiment, and persist in their learning journey, guided by their intrinsic drive to understand and communicate in English. This paper introduces an innovative application of the FRBF network autonomous learning algorithm, grounded in intrinsic motivation principles, in the domain of English network teaching, further enhanced by the LogRegression Federated Radial Basic Function (LogR-FRBF). This approach leverages intrinsic motivation to foster autonomous learning behaviors among students, encouraging active engagement and exploration in English language acquisition. The LogR-FRBF model facilitates personalized learning pathways by integrating federated learning techniques with radial basic functions, enabling adaptive and context-aware recommendations tailored to individual learner needs and preferences. Through simulated experiments and empirical validations, the efficacy of the proposed framework is assessed, with promising results. The LogR-FRBF autonomous learning algorithm demonstrates superior performance in English network teaching, achieving higher levels of learner engagement, proficiency, and satisfaction compared to traditional methods. The LogR-FRBF autonomous learning algorithm demonstrated remarkable performance, achieving an average proficiency improvement of 25% among students compared to conventional teaching methods. Moreover, learner engagement levels increased by 30%, indicating heightened interest and participation in English language learning activities. Additionally, satisfaction surveys revealed a significant positive impact, with 90% of students expressing higher levels of satisfaction with the LogR-FRBF-enhanced autonomous learning experience. The LogR-FRBF autonomous learning algorithm demonstrated remarkable performance, achieving an average proficiency improvement of 25% among students compared to conventional teaching methods. Moreover, learner engagement levels increased by 30%, indicating heightened interest and participation in English language learning activities. Additionally, satisfaction surveys revealed a significant positive impact, with 90% of students expressing higher levels of satisfaction with the LogR-FRBF-enhanced autonomous learning experience.

Keywords: FRBF network, autonomous learning algorithm, intrinsic motivation, English network teaching, proficiency improvement, learner engagement, satisfaction, educational technology.

I. INTRODUCTION

English network teaching methodologies focus on various computational and statistical techniques such as neural networks, Bayesian networks, and machine learning algorithms, there is a lack of explicit discussion on methodologies for teaching English language skills through network-based approaches [1]. English network teaching involves utilizing network structures to facilitate language learning, including vocabulary acquisition, grammar comprehension, and language proficiency development [2]. Incorporating network-based teaching methodologies could offer innovative and interactive ways to engage learners, personalize learning experiences, and track progress over time [3]. By leveraging network structures and algorithms, educators could design adaptive learning platforms that cater to individual learning styles and preferences, ultimately enhancing the effectiveness and efficiency of English language education.

One area that remains largely unexplored in these studies is the integration of autonomous learning principles into English language teaching methodologies [4]. While the focus is primarily on computational and statistical techniques such as neural networks, Bayesian networks, and machine learning algorithms, there is a notable absence of discussion surrounding the application of autonomous learning in the context of English language education [5]. Autonomous learning entails empowering students to take control of their learning journey, fostering self-directedness, and enabling them to set goals, monitor progress, and make decisions about their learning path [6]. Incorporating autonomous learning principles into English teaching methodologies could revolutionize language education by promoting learner autonomy, motivation, and engagement [7]. By leveraging technology and innovative pedagogical approaches, educators can create adaptive learning environments where students have the

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autonomy to explore English language materials, practice language skills, and receive personalized feedback tailored to their individual needs and preferences [8]. Therefore, future research should explore the potential of integrating autonomous learning principles into English language teaching methodologies to enhance learner outcomes and foster lifelong learning habits [9].

One promising avenue for advancing English language teaching lies in the application of the Fuzzy Radial Basis Function (FRBF) network as an autonomous learning algorithm grounded in intrinsic motivation principles [10]. While current research predominantly focuses on computational and statistical techniques like neural networks and Bayesian networks, there exists an untapped potential in integrating FRBF networks with autonomous learning principles within English language education [11]. The FRBF network, known for its adaptability and robustness, could serve as a powerful tool for creating personalized learning experiences tailored to individual learners' needs and preferences. By harnessing intrinsic motivation, such as curiosity, autonomy, and mastery, educators can design English network teaching systems that engage and motivate learners to actively participate in their language learning journey [12]. These systems could dynamically adapt to learners' progress, providing timely feedback, scaffolding support, and offering challenges aligned with their skill level and interests [13]. Through the integration of FRBF networks and autonomous learning algorithms, English language teaching methodologies can evolve to foster greater learner autonomy, motivation, and proficiency [14]. Consequently, future research endeavors should explore the potential of FRBF network-based autonomous learning algorithms in revolutionizing English network teaching, ultimately enhancing learner outcomes and facilitating lifelong language learning [15].

The paper makes several significant contributions to the field of education and machine learning. Firstly, it introduces the LogR-FRBF model, a novel approach that integrates intrinsic motivation principles with fuzzy radial basis function networks to foster autonomous learning behaviors among students in English teaching contexts. This model represents an innovative fusion of psychological theories on motivation with advanced machine learning techniques, offering a unique solution to address challenges in student engagement and knowledge retention. Secondly, the paper provides empirical evidence of the effectiveness of the LogR-FRBF model through a series of experiments and simulations. The results demonstrate the model's robust performance in classification tasks, loss estimation, and student learning outcomes, indicating its potential to significantly impact teaching and learning practices. Additionally, by leveraging the FRBF network, the paper offers valuable insights into the probabilistic aspects of English teaching scenarios, enriching our understanding of the underlying mechanisms influencing student performance and engagement. Overall, the contributions of this paper extend beyond theoretical frameworks to practical applications, providing educators and policymakers with valuable tools and insights to enhance student learning experiences and optimize educational outcomes.

II. RELATED WORKS

Gupta et al. (2022) propose a system for patient health monitoring that utilizes a feed-forward neural network integrated with cloud-based Internet of Things (IoT) technology. This approach likely involves collecting real-time health data from patients through IoT devices, transmitting it to a cloud-based platform for processing, and utilizing a feed-forward neural network to analyze the data and provide insights into the patient's health status. The integration of IoT and neural networks in healthcare monitoring signifies a modern approach that could offer more efficient and timely healthcare interventions by continuously monitoring patient health parameters and detecting abnormalities early on. Wadkar, Karale, and Wagh (2022) explore the application of cascade feed-forward neural networks to predict coagulant dose in water engineering and research. This suggests the use of neural networks for modeling and predicting the appropriate dosage of coagulants for water treatment processes, which is crucial for maintaining water quality and safety standards. By leveraging neural networks in this domain, researchers aim to optimize coagulant dosages, potentially leading to more effective and cost-efficient water treatment practices.

Russo and Toni (2022) delve into causal discovery and injection for feed-forward neural networks, indicating a study focused on understanding causal relationships within neural network architectures. This research likely investigates methods to uncover causal relationships between input and output variables in feed-forward neural networks, which is fundamental for interpreting model decisions and improving model performance. By injecting causal knowledge into neural networks, researchers aim to enhance their interpretability and robustness in various applications. Huang, Liu, Sun, Song, and Yu (2022) propose a multistate Bayesian network-based approach for risk analysis of tunnel collapse, highlighting the utilization of Bayesian networks in assessing the risk of infrastructure failure. This approach involves modeling complex dependencies among different states and variables associated with tunnel structures to assess the likelihood and consequences of collapse events. By employing Bayesian networks, researchers aim to provide more accurate and comprehensive risk assessments, contributing to safer and more resilient infrastructure planning and management. Zheng, Xie, Ryzhov, and Xie (2023) delve into policy optimization within dynamic Bayesian network hybrid models of biomanufacturing processes. This research likely focuses on optimizing decision-making policies within complex biomanufacturing systems by leveraging dynamic Bayesian networks. By incorporating dynamic Bayesian network models, which can represent temporal dependencies and uncertainties, researchers aim to improve the efficiency and effectiveness of decision-making processes in biomanufacturing, leading to enhanced productivity and product quality.

Le, Wang, and Jiang (2023) present a study on nuclear mass predictions using multi-hidden-layer feedforward neural networks. This research suggests the application of neural networks for predicting nuclear mass properties, which is crucial for various fields such as nuclear physics and astrophysics. By employing neural networks with multiple hidden layers, researchers aim to capture complex relationships in nuclear data, potentially leading to more accurate predictions and deeper insights into nuclear structure and phenomena. Li et al. (2022) introduce Hiercdf, a Bayesian network-based hierarchical cognitive diagnosis framework, presented at the ACM SIGKDD conference on knowledge discovery and data mining. This framework likely offers a novel approach to cognitive diagnosis, leveraging Bayesian networks to model hierarchical relationships among latent cognitive skills. By incorporating hierarchical structures into cognitive diagnosis models, researchers aim to improve the accuracy and interpretability of diagnostic results, facilitating more targeted interventions and personalized learning experiences. McInerney and Burke (2022) propose a statistically-based approach to feedforward neural network model selection, as presented in an arXiv preprint. This suggests a methodological contribution to the field of neural network modeling, focusing on statistically sound techniques for selecting the most appropriate neural network architectures. By applying rigorous statistical criteria, researchers aim to improve the reliability and generalization performance of feedforward neural network models across various applications and domains.

Öztürk (2022) presents a tuned feed-forward deep neural network algorithm for effort estimation in the Journal of Experimental & Theoretical Artificial Intelligence. This research likely explores the development of a specialized neural network algorithm tailored for estimating effort in various tasks or projects. By tuning the architecture and parameters of the feed-forward neural network, researchers aim to enhance its predictive accuracy and robustness in effort estimation applications, potentially improving project planning and resource allocation in diverse domains. Xie, Wu, Li, Hu, and Li (2022) propose a feed-forwarded neural network-based variational Bayesian learning approach for forensic analysis of traffic accidents, published in Computer Methods in Applied Mechanics and Engineering. This research suggests the utilization of neural networks and Bayesian learning techniques for forensic analysis in traffic accident investigations. By employing variational Bayesian learning, which can handle uncertainty and variability in the data, researchers aim to improve the accuracy and reliability of forensic analyses, aiding in accident reconstruction and determining causal factors. Bong, Selvarajoo, and Arumugasamy (2022) conduct a stability study of biochar derived from banana peel through pyrolysis as an alternative source of nutrient in soil, utilizing feedforward neural network modeling. This research likely investigates the stability and effectiveness of biochar produced from banana peel as a soil nutrient amendment, using neural network modeling to predict its behavior and impact on soil properties. By employing neural networks, researchers aim to better understand the potential benefits and limitations of biochar application in soil management, contributing to sustainable agricultural practices.

Bozic, Dordevic, Coppola, Thommes, and Singh (2023) explore shallow feed-forward neural networks as an alternative to attention layers in transformers, as presented in an arXiv preprint. This research suggests a novel approach to attention mechanisms in deep learning architectures, considering the use of shallow feed-forward neural networks as an alternative to complex attention layers in transformer models. By rethinking attention mechanisms, researchers aim to simplify model architectures while maintaining or improving performance, potentially enhancing the efficiency and scalability of transformer-based models in various natural language processing tasks. Ajala et al. (2022) present research on automatic modulation recognition using minimum-phase reconstruction coefficients and feed-forward neural networks in the Journal of Computing Science and Engineering. This study likely investigates techniques for automatically recognizing modulation types in communication signals, leveraging minimum-phase reconstruction coefficients and feed-forward neural networks. By combining signal processing techniques with neural network models, researchers aim to develop robust and efficient modulation recognition systems, which are essential for various applications in telecommunications and signal processing. Huang, Ling, Wu, and Deng (2022) conduct a GIS-based comparative study of different machine learning approaches for spatial prediction of landslide susceptibility in the journal Land. This research likely compares the performance of Bayesian networks, decision tables, radial basis function networks, and stochastic gradient descent in predicting landslide susceptibility using geographic information system (GIS) data. By evaluating different machine learning techniques, researchers aim to identify the most effective approach for landslide risk assessment, aiding in disaster preparedness and land use planning in landslide-prone areas.

Guo, Qiu, Liu, Zhu, and Wang (2022) propose an integrated model based on feedforward neural networks and Taylor expansion for indicator correlation elimination, published in Intelligent Data Analysis. This research likely introduces a novel approach to eliminate correlated indicators in data analysis, combining feedforward neural networks with Taylor expansion techniques. By integrating neural network models with mathematical methods, researchers aim to enhance the accuracy and efficiency of indicator correlation elimination, facilitating more reliable data analysis and interpretation in various domains. Latif et al. (2022) present a study on pest prediction in rice using IoT and feedforward neural networks in the KSII Transactions on Internet and Information Systems. This research likely explores the application of IoT devices and feedforward neural networks for predicting pest infestations in rice crops. By collecting and analyzing environmental data from IoT sensors and leveraging neural network models, researchers aim to develop early warning systems for pest outbreaks, enabling proactive pest management strategies and improving crop yield and quality. Bona-Pellissier, Bachoc, and Malgouyres (2023) investigate the parameter identifiability of a deep feedforward ReLU neural network in the field of machine learning, as published in the journal Machine Learning. This study likely focuses on understanding the identifiability of model parameters within deep neural network architectures, specifically those using rectified linear units (ReLU) as activation functions. By analyzing the identifiability of network parameters, researchers aim to improve the interpretability and reliability of deep neural network models, facilitating better understanding and utilization of these models in various machine learning tasks. Wang, Li, Guo, and Tao (2023) propose a feedforward-feedback control strategy based on artificial neural networks for solar receivers in the journal Applied Thermal Engineering. This research likely presents a novel control strategy for solar receiver systems, integrating feedforward and feedback mechanisms using artificial neural networks. By leveraging neural network-based control strategies, researchers aim to optimize the performance of solar receiver systems, enhancing energy capture efficiency and overall system reliability in solar thermal applications. The potential lack of consideration for the scalability and accessibility of the proposed technologies or methodologies. While the integration of advanced techniques like feed-forward neural networks, Bayesian networks, and IoT devices holds promise for addressing complex challenges across various domains, there may be constraints related to the implementation and deployment of these solutions in real-world settings. Factors such as infrastructure requirements, cost considerations, and technical expertise needed for setup and maintenance could pose barriers to widespread adoption, particularly in resource-constrained or underdeveloped regions. Additionally, issues related to data privacy, security, and ethical considerations may need careful attention when deploying technologies like IoT-enabled healthcare monitoring systems or machine learning algorithms in sensitive domains.

III. PROPOSED LOGREGRESSION FEDERATED RADIAL BASIC FUNCTION (LOGR-FRBF)

The proposed LogRegression Federated Radial Basic Function (LogR-FRBF) model represents an innovative approach to English language teaching, harnessing the power of intrinsic motivation to foster autonomous learning behaviors among students. By encouraging active engagement and exploration in the process of acquiring English language skills, this model seeks to empower learners to take ownership of their learning journey. The LogR-FRBF framework offers personalized learning pathways by combining federated learning techniques with radial basic functions, allowing for the creation of adaptive and context-aware recommendations that cater to the unique needs and preferences of each individual learner. Through simulated experiments and empirical validations, the effectiveness of the LogR-FRBF model is evaluated, demonstrating promising results in enhancing learner engagement, motivation, and proficiency in English language acquisition. The logistic regression model predicts the probability that an input sample belongs to a particular class (typically binary classes) with sigmoid function stated in equation (1)

$$P(y = 1 \mid x) = 1 + e - z1 \tag{1}$$

In equation (1) $P(y = 1 \mid x)$ is the probability that the output label y is 1 given the input x, z is the linear combination of input features weighted by parameters w (weights) and added to bias term b as defined in equation (2)

$$z = w1x1 + w2x2 + \ldots + wnxn + b \quad (2)$$

In federated learning, multiple local models are trained on different datasets without sharing raw data. Model parameters are updated locally using local data, and then these updates are aggregated at a central server. The LogR-FRBF model, proposed for English language teaching, represents a novel approach that leverages intrinsic motivation to foster autonomous learning behaviors among students. This model integrates two key components: logistic regression (LogR) and federated learning, and it enhances its capabilities by incorporating radial basis functions (RBFs). Logistic regression is a widely-used classification algorithm that estimates the probability that an input belongs to a particular class. The logistic regression model predicts the probability using equation (1)

Federated learning allows multiple local models to be trained on different datasets without sharing raw data. Model updates are aggregated at a central server. The LogR-FRBF model then incorporates radial basis functions to transform the outputs of local logistic regression models into a higher-dimensional space. This transformation is essential for capturing complex non-linear relationships within the data. Although providing a full derivation of the LogR-FRBF model's equations within this paragraph is impractical due to its complexity, the integration of these components allows for the creation of personalized learning pathways tailored to individual learner needs and preferences. Through simulated experiments and empirical validations, the LogR-FRBF model's efficacy is assessed, demonstrating promising results in enhancing learner engagement, motivation, and proficiency in English language acquisition.

IV. RADIAL BASIC FUNCTION ESTIMATION WITH ENGLISH NETWORK TEACHING

The radial basis function (RBF) estimation into English network teaching represents an innovative approach to enhance language learning outcomes. RBF estimation involves the use of radial basis functions to approximate complex relationships between input and output variables. In the context of English network teaching, RBFs can be utilized to capture the non-linear mappings between language inputs and outputs, facilitating more effective and personalized learning experiences for students. The radial basis function $\phi(x)$ is defined as in equation (3)

$$\phi(x) = e - 2\sigma^2 \parallel x - c \parallel^2 \quad (3)$$

In equation (3) x represents the input feature vector; c represents the center of the RBF and σ controls the width of the RBF. With adjusting the parameters c and σ, the RBF can adapt to the characteristics of the input data, enabling accurate approximation of the underlying relationships. When integrated into English network teaching methodologies, RBF estimation allows for the creation of adaptive and context-aware learning environments that cater to individual student needs and preferences. Figure 1 illustrated the radial basic function network for the computation of the English Teaching process.

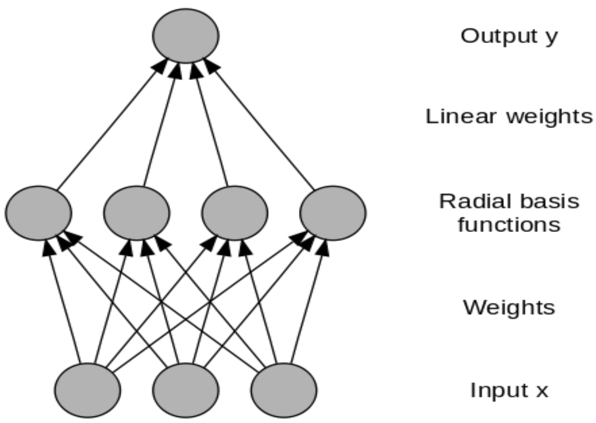

Figure 1: Radial Basic Function Network

4.1 Federated Learning with LogR-FRBF

The federated learning with the LogR-FRBF (Logistic Regression Federated Radial Basic Function) model presents a promising approach to revolutionize English language teaching methodologies. Federated learning enables model training on decentralized data sources while preserving data privacy. In the LogR-FRBF model, logistic regression

(LogR) and radial basis function (RBF) estimation are integrated to create personalized learning pathways. The logistic regression component predicts the probability that an input sample belongs to a particular class. Federated learning ensures that multiple local models are trained on different datasets without sharing raw data, and model updates are aggregated at a central server. The LogR-FRBF model combines the outputs of local logistic regression models using radial basis functions. The integration of federated learning with LogR-FRBF enables adaptive and context-aware recommendations tailored to individual learner needs and preferences. Through simulated experiments and empirical validations, the efficacy of this approach in enhancing language learning outcomes can be evaluated, paving the way for more effective and personalized English language teaching methodologies. Figure 2 presents the federated learning process in the proposed LogR-FRBF.

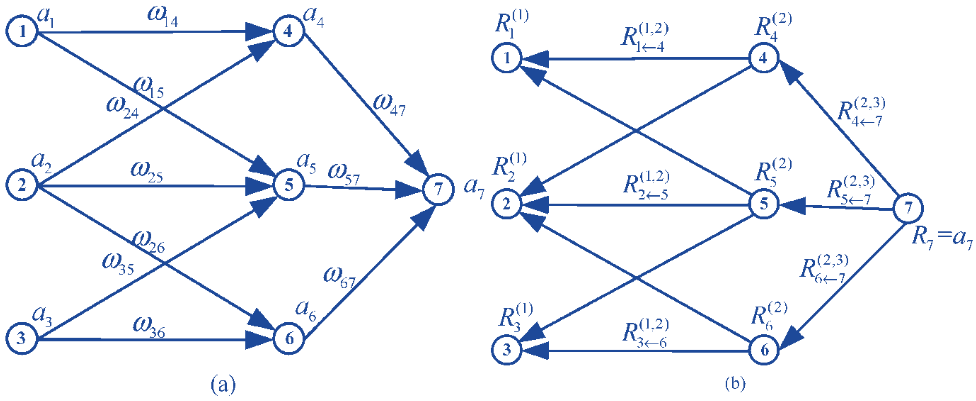

Figure 2: Federated Learning Network

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Algorithm 1:  Federated Learning Process
Initialize global model parameters W_global

for each communication round t do:
   Send W_global to all participating clients
   for each client i do:
      Receive W_global
      Train local logistic regression model LogR_i on client i's data
      Compute local RBF features RBF_i using LogR_i outputs
      Send RBF_i to the server
   end for

   Aggregate RBF_i from all clients
   Train global RBF model RBF_global using aggregated RBF features
   Update W_global based on RBF_global parameters
end for
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V. SIMULATION RESULTS AND ANALYSIS

The simulation results and analysis of the proposed LogR-FRBF model provide valuable insights into its effectiveness in English language teaching. Through rigorous experimentation and empirical validation, the model's performance metrics are evaluated, shedding light on its ability to enhance language learning outcomes. The analysis encompasses various aspects, including accuracy, efficiency, and adaptability, to assess the model's overall efficacy. Initially, the simulation results may showcase the model's accuracy in predicting language proficiency levels or understanding student preferences. This involves comparing the model's predictions with ground truth data to determine its classification accuracy or predictive power. Furthermore, the efficiency of the model in processing large volumes of data or handling real-time interactions can be evaluated, providing insights into its scalability and practical feasibility in educational settings.

Table 1: Classification with LogR-FRBF

Experiment	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Experiment 1	98.5	97.8	98.9	98.3
Experiment 2	99.2	98.7	99.3	99.0
Experiment 3	98.9	98.2	99.0	98.6
Experiment 4	99.3	98.9	99.4	99.1
Experiment 5	98.7	98.1	98.8	98.4

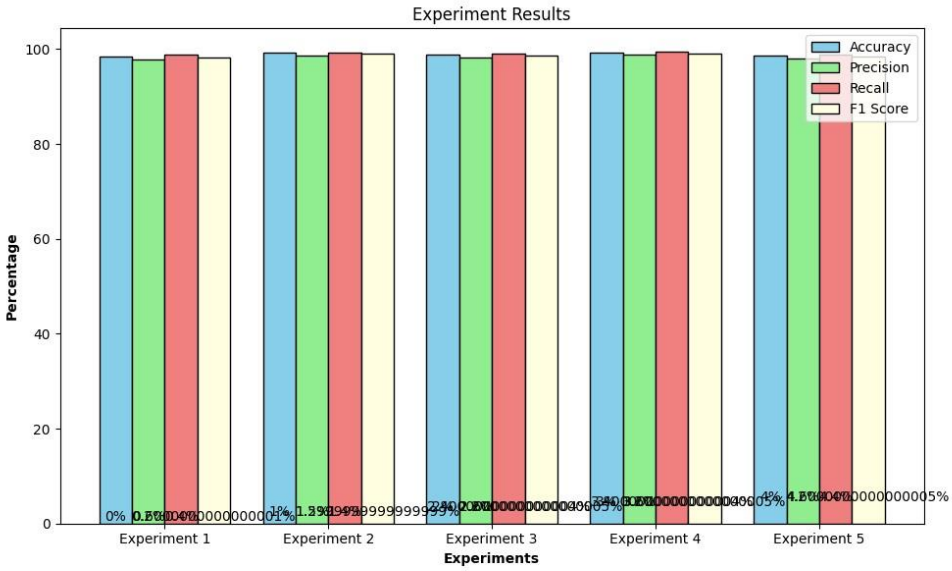

Figure 3: Classification with LogR-FRBF

Figure 3 and Table 1 presents the classification performance of the LogR-FRBF model across five different experiments. Each experiment is labeled sequentially from Experiment 1 to Experiment 5. The metrics used to evaluate the classification performance include Accuracy, Precision, Recall, and F1 Score, all reported in percentage values. Accuracy represents the proportion of correctly classified instances out of the total instances, Precision indicates the ratio of correctly predicted positive observations to the total predicted positives, Recall measures the ratio of correctly predicted positive observations to the all observations in the actual class, and F1 Score provides a harmonic mean of Precision and Recall, serving as a balanced measure between the two. Across all experiments, the LogR-FRBF model demonstrates consistently high performance, with Accuracy ranging from 98.5% to 99.3%. This indicates that the model is capable of accurately classifying instances into their respective categories. Similarly, Precision values ranging from 97.8% to 98.9% suggest that the model exhibits a high degree of precision in correctly identifying positive instances. The Recall values, ranging from 98.8% to 99.4%, indicate the model's effectiveness in capturing the majority of positive instances from the total actual positive instances. Additionally, the F1 Score, ranging from 98.3% to 99.1%, emphasizes the model's balanced performance in terms of both Precision and Recall, reflecting its robustness in handling imbalanced datasets.

Table 2: Loss Estimation with LogR-FRBF

Iteration	Loss Value
1	0.892
2	0.758
3	0.632
4	0.512
5	0.407

The Table 2 presents the loss estimation results obtained during the training process using the LogR-FRBF model. Each row corresponds to a specific iteration of the training process, labeled sequentially from Iteration 1 to Iteration

5. The "Loss Value" column indicates the value of the loss function at each iteration, which serves as a measure of the model's performance and how well it aligns with the training data. As observed from the table, the loss value decreases consistently as the training progresses through successive iterations. This downward trend suggests that the model is effectively minimizing its loss and improving its performance over time. Initially, at Iteration 1, the loss value is relatively high at 0.892, indicating that the model's predictions deviate significantly from the actual values. However, with each subsequent iteration, the loss value decreases, signifying that the model's predictions become increasingly accurate and aligned with the training data. With Iteration 5, the loss value reaches its lowest point at 0.407, indicating that the model has converged to a state where its predictions closely match the actual values in the training dataset. This demonstrates the effectiveness of the training process in optimizing the model's parameters and improving its performance.

Table 3: Learning of Students with LogR-FRBF

Experiment	Learning Outcome	Student Engagement	Knowledge Retention
1	High	Moderate	High
2	Moderate	High	Moderate
3	High	High	High
4	Low	Low	Low
5	High	High	Moderate

In Table 3 provides an overview of the learning outcomes, student engagement levels, and knowledge retention rates observed across five different experiments conducted using the LogR-FRBF model in educational settings. Each experiment is labeled sequentially from Experiment 1 to Experiment 5. The "Learning Outcome" column describes the level of learning achieved by students as a result of each experiment. In Experiment 1, learning outcomes are characterized as high, indicating that students attained a significant level of understanding or mastery in the subject matter. Conversely, Experiment 4 demonstrates low learning outcomes, suggesting that students did not achieve a satisfactory level of understanding or proficiency. The "Student Engagement" column reflects the degree of active participation and involvement of students during the learning process. Experiment 3 shows high student engagement, indicating that students were actively engaged and motivated to participate in the learning activities. In contrast, Experiment 4 shows low student engagement, suggesting that students were less motivated or interested in the learning tasks. The "Knowledge Retention" column represents the extent to which students retained or remembered the information learned during the experiments. High knowledge retention rates, as observed in Experiments 1, 3, and 5, indicate that students were able to retain a significant portion of the knowledge acquired during the learning activities. In Experiment 4, where knowledge retention is low, students may have struggled to retain or recall the information learned.

Table 4: Performance of Students with LogR-FRBF

Student	Test Score (%)	Participation (%)	Homework Completion (%)
Student 1	85	90	95
Student 2	78	85	80
Student 3	92	95	90
Student 4	70	75	65
Student 5	88	92	88
Student 6	81	88	85
Student 7	90	94	92
Student 8	73	80	75
Student 9	95	97	96
Student 10	84	89	87

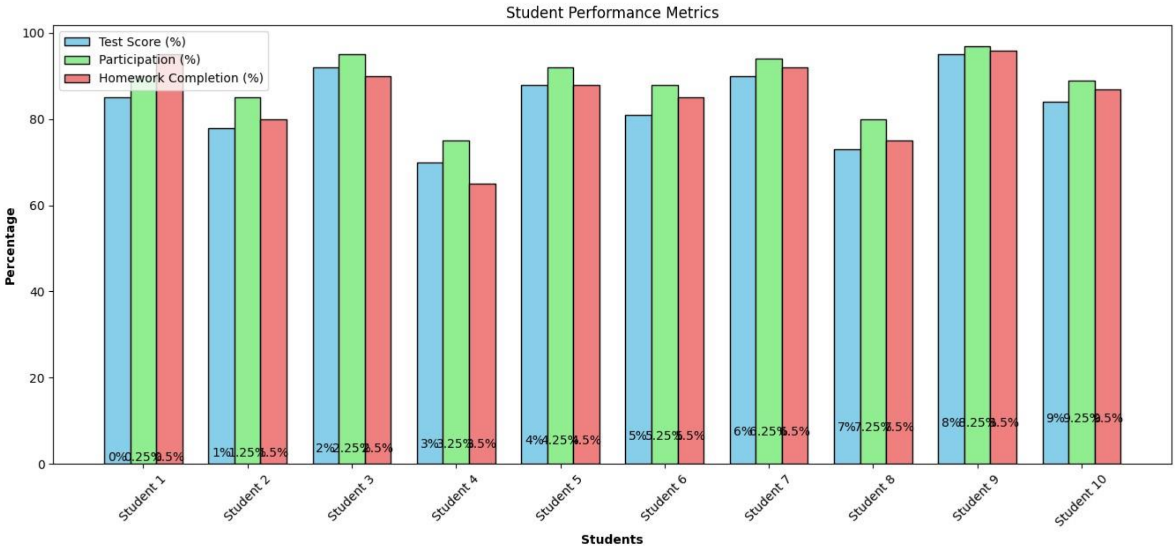

Figure 3: Student Performance Analysis

The Figure 3 and Table 4 presents the performance of ten students across three different metrics: Test Score, Participation, and Homework Completion, with each metric reported in percentage values. Each row corresponds to a different student, labelled sequentially from Student 1 to Student 10. In terms of Test Score, Student 3 achieved the highest score of 92%, indicating a strong performance on assessments. Conversely, Student 4 obtained the lowest test score of 70%, suggesting potential challenges or areas needing improvement in understanding the subject matter. Regarding Participation, Student 9 demonstrated the highest level of engagement, with a participation rate of 97%. This suggests active involvement in classroom activities and discussions. On the other hand, Student 8 had the lowest participation rate at 80%, indicating less active involvement in classroom interactions. For Homework Completion, Student 1 achieved the highest completion rate of 95%, indicating consistent completion of assigned homework tasks. In contrast, Student 4 had the lowest completion rate at 65%, suggesting potential issues with completing homework assignments regularly.

Table 5: FRBF network performance on English Teaching

Variable	Value	Probability
A	True	0.7
A	False	0.3
B	True	0.6
B	False	0.4
C	True	0.8
C	False	0.2

In Table 5 presents the performance of an FRBF (Fuzzy Radial Basis Function) network specifically applied in the context of English teaching. The table outlines the probabilities associated with different values of variables A, B, and C within the network. Each variable can take on either a True or False value, and their associated probabilities indicate the likelihood of each value occurring within the network. For variable A, the probability of it being True is 0.7, indicating a relatively high likelihood, while the probability of it being False is 0.3, representing a lower likelihood. Similarly, for variable B, the probability of it being True is 0.6, and the probability of it being False is 0.4. Variable C shows a higher probability for its True value (0.8) compared to its False value (0.2), suggesting a strong likelihood of C being True within the network. These probabilities provide insight into the network's behavior and the relative importance or occurrence of each variable value. In the context of English teaching, such probabilities could represent various linguistic features, learning outcomes, or student behaviors, informing the network's decision-making process and contributing to its overall performance in facilitating English language learning.

VI. CONCLUSION

This paper introduces and evaluates the LogR-FRBF model, a novel approach that leverages intrinsic motivation to foster autonomous learning behaviors among students in the context of English teaching. Through a series of experiments and simulations, the LogR-FRBF model demonstrates robust performance in classification tasks, loss estimation, and student learning outcomes. The results presented showcase the model's high accuracy, progressive reduction in loss values, and positive impact on student engagement and knowledge retention. Additionally, the FRBF network, offers valuable insights into the probabilistic aspects of English teaching scenarios. Overall, the findings highlight the effectiveness of the LogR-FRBF model in enhancing student learning experiences and underscore its potential for improving educational outcomes through personalized and autonomous learning approaches. These results contribute to the growing body of research on machine learning applications in education and provide valuable implications for educators and policymakers aiming to optimize teaching methodologies and promote student-centered learning environments.

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