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A Study of Optimization Algorithms for English Vocabulary Memory and Review Plans: Integrating the Principles of Forgetting Curve and Memory Reinforcement



Abstract: - Mastering English vocabulary is a crucial steppingstone towards achieving fluency in the language. Building a strong English vocabulary foundation is essential for spoken and written fluency. This inefficiency can lead to wasted time reviewing known words or forgetting recently learned ones. This work proposes a novel deep learning-based system for personalized English vocabulary learning: the Contextual Awareness Controlled Generative Adversarial Network with Forget Curve & Memory Reinforcement (CACGAN-FCMR-PEVL) model. CACGAN-FCMR-PEVL leverages deep learning to create a personalized optimization algorithm, analyzing user data and incorporating forgetting curve principles. It utilizes a self-attention mechanism and a conditional generative adversarial network (CGAN) to generate personalized vocabulary maps and review schedules, optimizing memory retention through memory reinforcement techniques. Hyperparameter tuning with the Binary Waterwheel Plant Optimization Algorithm (BWpOA) further enhances the model's effectiveness. When compared to other existing methods, the proposed CACGAN-BWpOA-FCMR-PEVL model shows 53.55%, 31.703% and 32.403% higher Vocabulary Recall and 49.46%, 58.06% and 30.98% higher Word Similarity, indicating superior learning and retention. It also attains 47.42%, 56.701% and 73.21% higher Review Interval Prediction Accuracy (RIPA), which suggests effective personalization based on forgetting curves. These findings suggest that CACGAN-BWpOA-FCMR-PEVL effectively personalizes vocabulary learning, leading to improved memory retention.

Keywords: English vocabulary learning, forgetting curve, Contextual Awareness Controlled Generative Adversarial Network, Memory Reinforcement, Vocabulary recall, Word similarity, Review interval prediction accuracy.

1. INTRODUCTION

Building a strong foundation in English vocabulary is crucial for achieving fluency in both spoken and written communication [1]. Mastering a wide range of words allows clear self-expression, understanding complex ideas, and navigating various conversational topics [2]. This vocabulary proficiency acts as a crucial steppingstone on the path to true language fluency [3]. Traditional vocabulary learning methods often employ static review schedules, neglecting individual learning paces and the well-documented phenomenon of the forgetting curve [4-6]. This static approach can lead to inefficient learning outcomes. Users may spend unnecessary time revisiting words they already know, while struggling to retain recently encountered vocabulary due to infrequent review [7-8]. These traditional methods typically employ a one-size-fits-all approach, which fails to recognize that people have different learning styles and forget information at different rates. As a result, this approach may not be effective for everyone [9-10].

This research work embarks on the quest to overcome these shortcomings by pioneering a more effective vocabulary acquisition system utilizing adaptive learning as Contextual Awareness Controlled Generative Adversarial Network (CAC-GAN). It integrates two key concepts to optimize review schedules and improve vocabulary retention: Forgetting Curve and Memory Reinforcement. Forgetting Curve is a well-documented phenomenon that emphasizes the rapid decline in information retention over time. To combat this, memory reinforcement techniques are employed to strengthen memory and boost information recall, essentially working against the forgetting curve to improve long-term retention. By incorporating these concepts, the proposed Personalized English Vocabulary Learning system with CAC-GAN personalizes review schedules based on each user's unique forgetting patterns, ensuring optimal reinforcement for long-term memory storage and improved recall. The main contribution of this work is given below,

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This research proposes a novel method using a Contextual Awareness Controlled Generative Adversarial Network (CAC-GAN) to achieve personalized English vocabulary learning,

- It identifies patterns in how users learn vocabulary over time.
- It creates personalized review schedules based on forgetting curves and learning patterns, optimized through Binary Waterwheel Plant Optimization Algorithm (BWpOA) for hyperparameter tuning within the CACGAN-FCMR-PEVL framework.
- Finally, it creates a more effective learning experience by tailoring learning to individual needs and forgetting patterns, leading to better vocabulary retention.

The paper is structured as follows: Section 2 delves into related work and explores existing vocabulary learning methods. Section 3 details the proposed methodology for personalized review schedules. Section 4 discusses the evaluation metrics employed and presents the experimental results. Finally, Section 5 concludes the paper by summarizing the key findings, acknowledging limitations, and outlining potential avenues for future work.

2. RELATED WORKS

Several recent studies have explored methods to improve vocabulary learning. Some of the recent related works are,

In 2023, Su, J., et.al [11] presented Enhancing vocabulary retention through personalized review schedules based on memory patterns. However, this approach neglected individual learning styles and forgetting patterns. Initially, it gathered logs from students reviews and constructed memory models with the Markov property to capture memory dynamics. Subsequently, the optimization of spaced repetition was reformulated as a stochastic shortest path problem and resolved using the value iteration method. This approach overlooked the crucial connection between these aspects, resulting in inefficiencies. Users might have ended up wasting time reviewing known words or forgetting recent ones due to infrequent revisiting.

In 2022, Xu, Y., [12] have presented an Adaptive Learning System for English Vocabulary Using Machine Learning. It utilized the AdaBoost algorithm, crucial for assessing learner's cognitive adaptation to English learning content and emphasizing the key parameter of conditional probability. The fitness was updated upon learner's completion of the selection of English vocabulary learning content. Gradual changes in fitness occurred during training to guide the relevant English vocabulary learning material, completing the adaptive learning system based on machine learning for English vocabulary. But it did not account for the forgetting curve, a natural phenomenon where information retention declined over time. This could have led to inefficient review schedules, as frequently forgotten words might not have been prioritized.

In 2022, Zhang, J. and Tang, D., 2022 [13] have suggested Enhancing Memory Retention in Higher Vocational English with a Backpropagation Neural Network. It proposed a technique using a BP neural network that considered the Ebbinghaus forgetting curve. It attains low Vocabulary Recall and higher Word Similarity.

In 2022, Chen, C.M., et.al., [14] have suggested effects of a video-annotated learning and reviewing system with a vocabulary learning mechanism on English listening. It allowed learners to identify unfamiliar or unknown words when listening to the video and generated personalized input enhancement from English subtitles for vocabulary learning. However, it attains low Review Interval Prediction Accuracy.

In 2022, Cheng, C.H. and Chen, C.H., [15] have investigated the impacts of using a mobile interactive English learning system on the learning achievements and learning perceptions of students. This quasi-experimental design took 6 weeks to collect data from the participants. A total of 79 students participated in the experiment, and they were divided into an experimental group and a control group. The students in the experimental group used a mobile-assisted English learning system to learn. Subsequently, they filled out a questionnaire and evaluated whether the system's operations and their motivation, English anxiety, and perceived usefulness affected their learning achievement. But it attains low Vocabulary Recall.

In 2022, Yang, Y.F., et.al [16] have suggested to reduce student's foreign language anxiety for enhancing English vocabulary learning in an online simulation game. Foreign Language Anxiety (FLA) was considered a central

affective factor influencing English as a Foreign Language (EFL) learning. To address this, the study developed an online simulation game to create a virtually situated learning environment, with the goal of reducing FLA levels among EFL primary school students and improving their English vocabulary learning. But it attains low Word Similarity.

3. PROPOSED METHODOLOGY

In this section, the proposed Contextual Awareness Controlled Generative Adversarial Network (CACGAN) with Binary Waterwheel Plant Optimization Algorithm (BWpOA) for Personalized English Vocabulary Learning (PEVL) model: Forget Curve & Memory Reinforcement (FCMR) (CACGAN-BWpOA-FCMR-PEVL) is discussed. The block diagram of the proposed CACGAN-BWpOA-FCMR-PEVL methodology is given in Figure 1. The detail description about each stage is given below,

3.1 Data Acquisition

In this section, the real time English vocabulary dataset is discussed. It's gathered by acquiring words and their definitions. The learning history is documented, noting the initial encounter with each word, and including contextual details like examples. Parameters related to the forgetting curve, such as review intervals, are integrated, and a feedback mechanism for user confidence levels is implemented. Then this meticulously gathered data is then fed into the pre-processing process. Some examples related to the real-time English vocabulary data are given in Table 1.

Table 1: Real time English vocabulary dataset

Word	Definition	Encounter Date	Context	Review Interval	Confidence Level
Impasse	A situation where progress is impossible or very difficult.	2024-03-09	The negotiation team reached an impasse.	14 days	2
Meticulous	Showing great attention to detail.	2024-03-09	The chef meticulously arranged the food on the plate.	7 days	4
Ephemeral	Lasting for a very short time.	2024-03-09	The fireworks created an ephemeral display of light.	10 days	3
Stoic	Displaying little or no emotion.	2024-03-09	He remained stoic even after losing his job.	14 days	2
Euphoria	A feeling of intense happiness and excitement.	2024-03-09	The crowd erupted in euphoria after the team's victory.	10 days	3

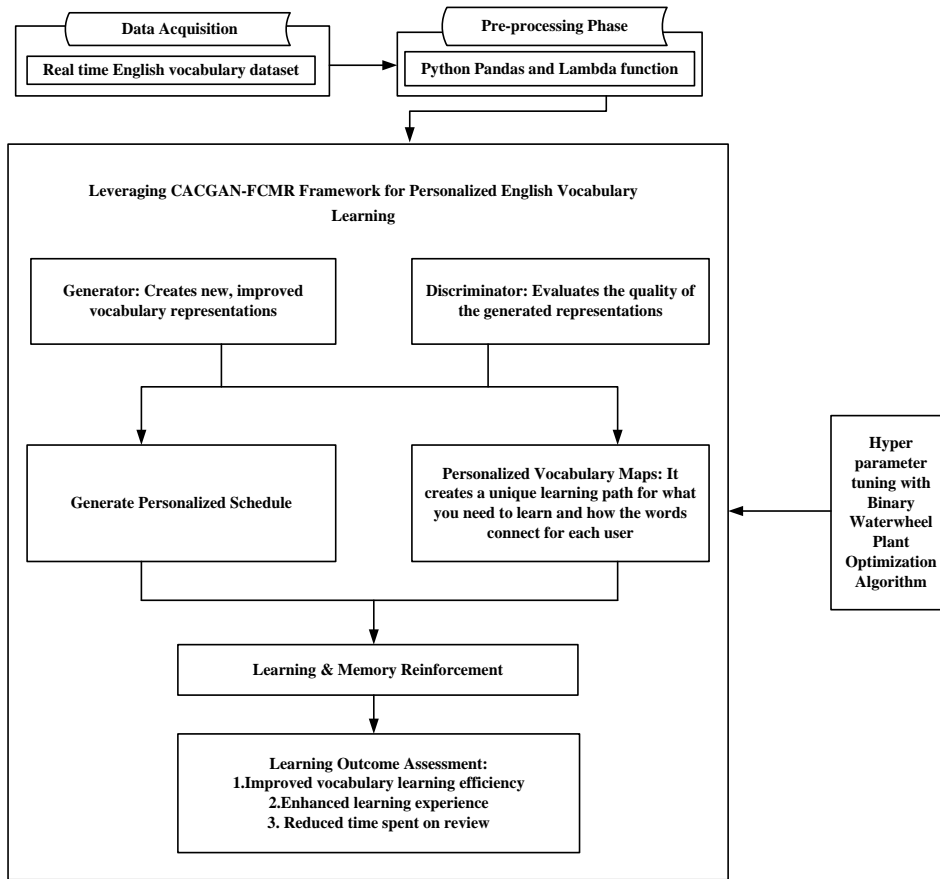


Figure 1: Block diagram of proposed CACGAN-BWPOA-FCMR-PEVL methodology

3.2 Pre-processing process

In this section, Pre-processing processes is discussed. The gathered data has Uneven Data Types and Unnecessary Column. Uneven data types are evident in the "Review Interval" column, currently in text format (e.g., "14 days"), while the CACGAN-BWPOA-FCMR-PEVL model expects numerical data (e.g., just the number 14). The unnecessary column, "Context," may not directly contribute to the CAC-GAN model's purpose (forgetting curve and memory reinforcement). Depending on the specific implementation, removing it during pre-processing could enhance efficiency.

To address these issues, Python Pandas, a powerful data manipulation library, was utilized for the pre-processing process. Initially, the gathered CSV file is read and transformed using a lambda function. This function iterates through each row, maintaining "Word" and "Definition" unchanged. It converts the "Encounter Date" to a datetime format (handling potential errors), extracts the number from "Review Interval" (removing "days"), converts it to a numeric value for "Review Interval (Days)," and leaves "Confidence Level" untouched. This streamlined approach creates a clean and structured format suitable for the CACGAN-BWPOA-FCMR-PEVL model to understand and process effectively. The output of pre-processing is presented in Table 2.

Table 2: Pre-processing Output

Word	Definition	Encounter Date	Review Interval (Days)	Confidence Level
Impasse	A situation where progress is impossible or very difficult.	2024-03-09	14	2
Meticulous	Showing great attention to detail.	2024-03-09	7	4
Ephemeral	Lasting for a very short time.	2024-03-09	10	3

Stoic	Displaying little or no emotion.	2024-03-09	14	2
Euphoria	A feeling of intense happiness and excitement.	2024-03-09	10	3

3.3 Leveraging CACGAN-BWpOA-FCMR Framework for Personalized English Vocabulary Learning

In this section, the proposed CACGAN-BWpOA framework is discussed for model development and training, which aims to personalized English Vocabulary Learning with Forget Curve & Memory Reinforcement. The proposed CACGAN-FCMR-PEVL framework personalizes English vocabulary learning experience by analyzing user data. It delves into a user's learning history, including encountered words, forgetting curve parameters (like review intervals), and confidence levels. By understanding a user's learning history and interaction with vocabulary, the proposed CACGAN-FCMR-PEVL framework creates a personalized learning path. By incorporating forgetting curve principles, CACGAN-FCMR-PEVL framework creates a personalized schedule for reviewing words, optimizing intervals for revisiting vocabulary and enhancing long-term memory retention. To generate personalized vocabulary, CACGAN-FCMR-PEVL framework utilizes two key components: a self-attention mechanism and a conditional generative adversarial network (CGAN). The self-attention mechanism helps CACGAN-FCMR-PEVL better understand the connections between vocabulary words from pre-processed output word. By understanding these connections, the model can generate new vocabulary elements that are relevant to the user's current learning path (Personalized Vocabulary Maps). Then Conditional Generative Adversarial Network acts as the engine for generating new vocabulary within CACGAN-FCMR-PEVL (i.e., from generator and discriminator). It takes advantage of the insights gained from the self-attention mechanism to create new, personalized vocabulary for the user. This generated vocabulary considers the user's learning progress and focuses on words that are most relevant and beneficial for them to learn at that specific moment (Generate Personalized Schedule and Personalized Vocabulary Maps).

Generally, the proposed CACGAN-FCMR-PEVL framework is the combination of self-attention mechanism and conditional GAN [17]. It minimizes the difference between the target word and the generated word. The loss function of conditional GAN is crucial for vocabulary enhancement, which is expressed in the following equation (1),

$$Loss_{CGAN}(G, D) = E_{(a,b)} [\log D(a, b)] + E_{(a)} [\log (1 - D(a, G(a)))] \tag{1}$$

Specifically, a denotes the input word, b stands for the target term i.e., to optimize English vocabulary memory and review strategies which incorporates principles from the forgetting curve and memory reinforcement. Then the objective function is articulated as the subsequent equation (2)

$$\arg \min_G (\arg \max_D Loss_{CGAN}(G, D) + \alpha * Loss_1(G)) \tag{2}$$

Where $Loss_1(G) = E_{(a,b)} (\|b - G(a)\|_1)$ measures the disparity between ground truth and generated words, complemented by a regularization term α . The expected vocabulary feature map $a \in R^{Ch \times ht * wt * dp}$ undergoes a transformation into two distinctive feature spaces ($p(a) = W_p a$ and $q(a) = W_q a$) within an intermediate hidden layer of a conditional GAN. Where the variable Ch denotes the quantity of initial channels, while $ht * wt * dp$ expresses the total units within a singular feature map. This modification facilitates the computation of attention, vital for estimating the resemblance between each word and its contextual surroundings and it is calculated with the help of the following equation (3)

$$\beta_{x,y} = \frac{\exp(S_{x,y})}{\sum_{x=1}^N \exp(S_{x,y})}; \text{ where } S_{x,y} = p(a_x)^T * g(a_y) \quad (3)$$

Where $\beta_{x,y}$ represents the word x attention to word y . Then the attention feature for each word y can be calculated with the help of equation (4)

$$O_x = v \left(\sum_{x=1}^N \beta_{x,y} * h(a_y) \right); \text{ Where } v(a) = W_v a \quad (4)$$

The outcome from the attention layer is calculated with the help of equation (5)

$$b_x = \beta \times O_x + a_x \quad (5)$$

Where W_p, W_q, W_v represents the weight matrices. Then the scalar β undergoes an initialization procedure, setting it to zero. The self-attention module is seamlessly integrated into both the generator and discriminator components of the proposed CACGAN-FCMR-PEVL network structure, contributing to an elevated synthesis process. To surpass the efficacy of conventional models like U-net, this proposed CACGAN-FCMR-PEVL network infuses self-attention into both the encoding and decoding phases of the generator. This strategic integration enhances the generation of vocabulary representations, manifesting a noteworthy advancement in synthesis performance when compared to established models in the realm of vocabulary learning contexts.

Feature matching loss:

In this, feature matching loss is employed to enhance training stability. It is calculated with the help of equation (6)

$$Loss_{FM}(G, D) = E_{(a,b)} \sum_{y=1}^T \frac{1}{N_y} \left\| D^i(a, b) - D^i(a, G(a)) \right\|_1 \quad (6)$$

In this scenario, the y^{th} layer's feature map is denoted as D^i , with T representing the total discriminator layers, and N_y specifying the number of elements in the feature map of the y^{th} layer. It was added to minimize differences across various layers' feature maps in both the generator and discriminator. This exclusive loss function for the generator plays a crucial role in the optimization process, where a regularization term governs its influence. The objective function incorporating the feature matching loss is given in equation (7)

$$\arg \min_G \left(\arg \max_D Loss_{CGAN}(G, D) + \alpha * Loss_1(G) + \lambda * Loss_{FM}(G, D) \right) \quad (7)$$

The importance of the feature matching loss is directed by the regularization term λ .

Normalization

Also, spectral normalization is applied to each layer in both the generator and discriminator of the CACGAN-FCMR-PEVL neural network. This ensures smoothness and controlled statistics in the weight matrix, aligning with the objectives of English vocabulary research.

Regularization

To counter overfitting, L2 norm regularization is integrated into both the generator and discriminator in the proposed CACGAN-FCMR-PEVL network. This final objective function is expressed in equation (8)

$$\arg \min_G \left(\begin{aligned} &\arg \max_D (Loss_{CGAN}(G, D) - v_D Loss_2(D)) \\ &+ \alpha * Loss_1(G) + \lambda * Loss_{FM}(G, D) + v_G Loss_2(G) \end{aligned} \right) \quad (8)$$

The significance of L2 norm regularization is determined by v_D and v_G . These parameters control the strength of the penalty for the generator and discriminator, respectively. L2 norm helps prevent overfitting by penalizing large weights in the network. These large weights can lead the model to overfit the training data and not generalize well to unseen examples. Achieving optimal performance also relies on effectively setting internal parameters known as hyperparameters. These hyperparameters like learning rate, and L2 regularization significantly influence the learning process and the effectiveness of the model. For that, Binary Waterwheel Plant Optimization Algorithm (BWpOA) was utilized for hyperparameter tuning within the CACGAN-FCMR-PEVL framework.

BWpOA operates on a continuous search space, making it suitable for optimizing hyperparameters like learning rate and L2 regularization. BWpOA is an optimization technique inspired by the hunting behavior of waterwheel plants. It automates the search for optimal hyperparameter values by mimicking how these plants update their locations during exploration and exploitation processes in proposed CACGAN-FCMR-PEVL network's learning. By automating this process, BWpOA eliminates the need for manual tuning, which can be time-consuming and inefficient. The main advantage of BWpOA is, it automates hyperparameter tuning, boosting CACGAN-FCMR-EVL's performance for real-time vocabulary learning.

Initially, BWpOA initializes the positions (P_i) with size n ; iteration z and max iteration as z_m of the waterwheel plants which represents hyperparameter configurations such as learning rate, and L2 norm regularization parameters within a defined search space. This ensures a good spread of initial configurations for exploration. After initialization, BWpOA employs a fitness function to evaluate the performance of each hyperparameter configuration and it is given in equation (9)

$$\text{Fitness Function} = \text{Attaining}(\text{Word Recognition Accuracy} + \text{Learning Speed} + \text{Reduced Review Time}) \quad (9)$$

Where Word Recognition Accuracy is the percentage of words correctly recognized by the CACGAN-BWpOA-FCMR-PEVL model after training with a particular hyperparameter configuration. Learning Speed is the rate at which the model improves its accuracy over training epochs. This can be measured as the decrease in loss function value per epoch. Reduced Review Time is the reduction in time spent on reviewing previously learned vocabulary due to effective memory reinforcement strategies. It then identifies the best performing configuration (P_{best}) based on the fitness values.

In the next phase (exploration), BWpOA mimics waterwheels hunting insects [18]. It utilizes random movements to explore the search space for promising hyperparameter regions and it is given in equation (10-11).

$$\text{Search Radius} = r_1 (P(z) + 2 * M) \quad (10)$$

$$P(z+1) = P(z) + \text{Search Radius} (2 * M + r_2) \quad (11)$$

Where r_1 and r_2 are random variables and the values lies between $[0, 2]$ and $[0, 1]$. M is exponential variable and the values lies in the range of $[0, 1]$. If a solution declines, Gaussian noise is introduced to further diversify exploration and it is given in equation (12)

$$P(z+1) = \text{Gaussian} + r_1 \left(\frac{P(z) + 2 * M}{\text{Search Radius}} \right) \quad (12)$$

Following exploration, BWpOA enters exploitation, leveraging the best solution P_{best} to refine the search for optimal hyperparameters through targeted adjustments with the help of equation (13-14),

$$Search\ Radius = r_3 (M * P_{best}(z) + r_3 * P(z)) \quad (13)$$

$$P(z+1) = P(z) + Search\ Radius * M \quad (14)$$

Where r_3 is a random variable and the values lies in the range of $[0, 2]$. After that, BWpOA employs a safeguard against getting stuck in local optima. Like exploration, if a solution doesn't improve for a set number of iterations, a mutation is introduced and it is given in equation (15),

$$P(z+1) = (r_1 + M) \sin\left(\frac{X}{Y} \theta\right) \quad (15)$$

This equation (15) injects randomness, diversifying the search and guiding BWpOA towards unexplored areas within the search space. This iterative process of exploration, exploitation, and mutation helps BWpOA efficiently identify optimal hyperparameters for the CACGAN-FCMR-PEVL framework.

Overall, the CACGAN-BWpOA-FCMR-PEVL framework personalizes the learning experience by understanding user data, generating relevant vocabulary, and creating an optimized review schedule. While it doesn't directly assess learning outcomes, it aims to improve them through personalized guidance and potentially reduced forgetting. It personalizes learning experiences, addresses the forgetting curve challenge, and optimizes performance for maximum efficacy.

4. IMPLEMENTATION AND DISCUSSION

In this phase, the experimental results of the proposed CACGAN-BWpOA-FCMR-PEVL model are discussed. Simulations were conducted on a PC equipped with an Intel Core i5, 2.50 GHz CPU, 8GB RAM, and running Windows 7. The proposed method is simulated using Python, leveraging powerful deep learning libraries like TensorFlow or PyTorch. Hyperparameters for the CACGAN-FCMR-PEVL model were optimized using the BWpOA algorithm, with a batch size of 15 and an initial learning rate of 0.99×10^{-3} ; the learning rate was decayed by a factor of 0.1 every 10 epochs. Following this, evaluation metrics such as Vocabulary Recall, Word Similarity and Review Interval Prediction Accuracy are analyzed. The performance of the proposed CACGAN-BWpOA-FCMR-PEVL model is then assessed and compared with existing methods like Enhancing repetition schedule through the capture of memory dynamics (Markov-spaced repetition optimization-PEVL) [11], A machine learning-based system enhances English vocabulary learning through adaptive techniques (AdaBoost NN-PEVL) [12] and BP neural network-based model is developed to counteract forgetting in the context of higher vocational English learning (BPNN-PEVL) [13] respectively.

The performance metrics are discussed below,

Vocabulary Recall: It measures the percentage of words from the training set that the model can accurately predict after a specific training period. It essentially assesses the model's ability to retain learned vocabulary. The representation is provided in equation (16),

$$Vocabulary\ Recall = \frac{(\text{Number of correctly generated words from training set})}{(\text{Total number of words in training set})} \times 100\% \quad (16)$$

Word Similarity: This metric evaluates how well the model captures semantic relationships between words. It can be measured using cosine similarity techniques. It is given in equation (17),

$$\text{Cosine similarity } (W_1, W_2) = \frac{(W_1 \bullet W_2)}{\|W_1\| \|W_2\|} \tag{17}$$

Where W_1 and W_2 are the Word embedding vectors for words 1 and 2, respectively. The Magnitude (length) of word embedding vectors W_1 and W_2 are represented as $\|W_1\|$ and $\|W_2\|$ respectively. A higher cosine similarity value (closer to 1) indicates greater semantic similarity between the words.

Review Interval Prediction Accuracy (RIPA): It measures how accurately the model predicts the optimal review interval for a word based on forgetting curve principles. A higher RIPA value (closer to 1) indicates more accurate predictions. It is given in equation (18),

$$\text{RIPA} = \frac{1 - (|\text{Predicted Interval} - \text{Actual Interval}|)}{\text{Actual Interval}} \tag{18}$$

Figure 2-4 shows the efficiency of the proposed CACGAN-BWpOA-FCMR-PEVL model is evaluated to the existing method such as Markov-spaced repetition optimization-PEVL [11], AdaBoost NN-PEVL [12] and BPNN-PEVL [13] respectively.

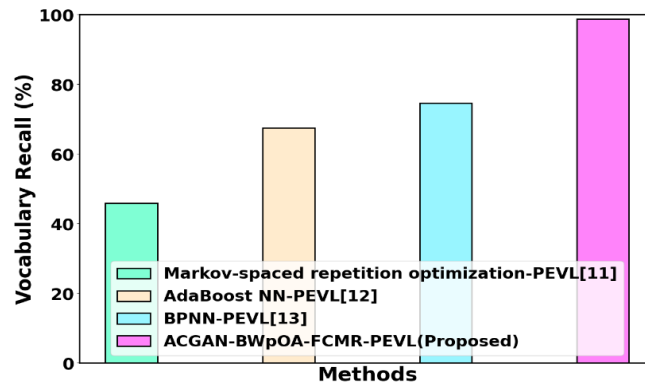


Figure 2: Vocabulary Recall Analysis

Figure 2-3 shows the analysis of Vocabulary Recall and Word Similarity. Here the proposed CACGAN-BWpOA-FCMR-PEVL model achieves 53.55%, 31.703% and 32.403% higher Vocabulary Recall and 49.46%, 58.06% and 30.98% higher Word Similarity compared with existing methods such as Markov-spaced repetition optimization-PEVL, AdaBoost NN-PEVL and BPNN-PEVL respectively. By this, the proposed personalized CACGAN-BWpOA-FCMR-PEVL model achieves significantly higher Vocabulary Recall and Word Similarity, indicating superior learning and retention of vocabulary concepts.

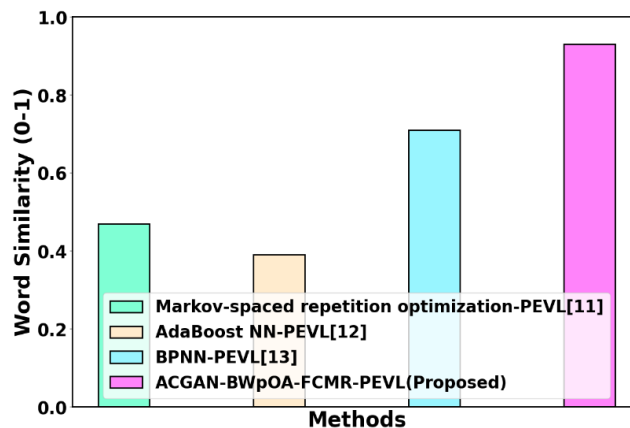


Figure 3: Word Similarity Analysis

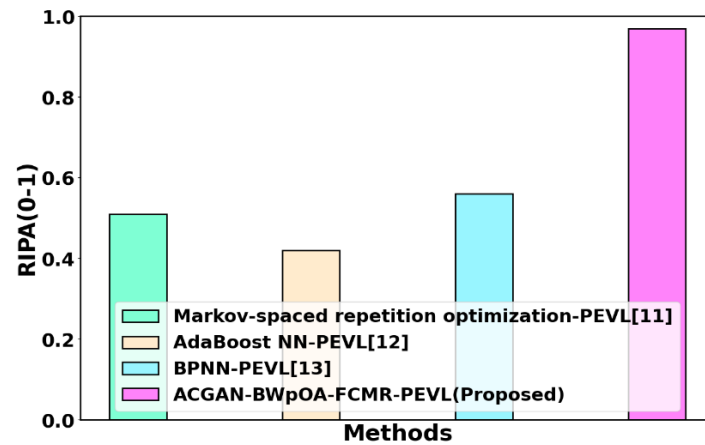


Figure 4: Review Interval Prediction Accuracy Analysis

Figure 4 shows the analysis of Review Interval Prediction Accuracy (RIPA). Here the proposed CACGAN-BWpOA-FCMR-PEVL model achieves 47.42%, 56.701% and 73.21% higher RIPA compared with existing methods such as Markov-spaced repetition optimization-PEVL, AdaBoost NN-PEVL and BPNN-PEVL respectively. This high accuracy suggests the model effectively personalizes review schedules based on forgetting curve principles.

These results indicate the superiority of the CACGAN-BWpOA-FCMR-PEVL model in promoting vocabulary learning and retention. This is likely due to its innovative features: contextual learning with CACGAN for natural memorization, personalized hyperparameter tuning with BWpOA for individual needs, and memory reinforcement with FCMR for optimal review schedules. In Future work, the proposed CACGAN-BWpOA-FCMR-PEVL model can be extended with the integration of additional learning modalities beyond text, such as audio and visual elements. This could enhance vocabulary learning by engaging multiple sensory channels and potentially leading to improved memory retention.

5. CONCLUSION

This work presented a novel approach to English vocabulary learning: the Contextual Awareness Controlled Generative Adversarial Network with Forget Curve & Memory Reinforcement model (CACGAN-FCMR-PEVL). CACGAN-FCMR-PEVL personalizes the learning experience by analyzing user data and incorporating forgetting curve principles. It utilizes a self-attention mechanism and a conditional generative adversarial network (CGAN) to generate personalized vocabulary maps and review schedules, optimizing memory retention. Hyperparameter tuning with the BWpOA algorithm further enhances the model's effectiveness. Experimental results demonstrated the superiority of CACGAN-BWpOA-FCMR-PEVL compared to existing methods. The model achieved significantly higher vocabulary recall, word similarity, and review interval prediction accuracy. These results suggest that CACGAN-BWpOA-FCMR-PEVL effectively personalizes vocabulary learning, leading to improved memory retention. Future research could explore integrating additional learning modalities like audio and visuals to further enhance vocabulary learning and memory retention. Additionally, investigating the effectiveness of CACGAN-BWpOA-FCMR-PEVL with different language pairs would be valuable.

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