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Design and Evaluation of English Vocabulary Learning Aids Based on Word Vector Modelling

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Abstract: **-** English vocabulary learning aids based on word vector modeling involve creating tools that leverage advanced techniques to enhance vocabulary acquisition. Word vector modeling, often using methods like Word2Vec or GloVe, represents words as high-dimensional vectors capturing semantic relationships. These models can power vocabulary learning aids by offering context-based word suggestions, personalized word quizzes, or interactive visualizations of word associations.. The paper introduces the Hierarchical Spiking Vocabulary Deep Learning (HSV-DL) framework, a novel approach aimed at enhancing vocabulary learning and classification tasks. With word vector modeling and spiking neural networks, HSV-DL offers a sophisticated methodology for accurately categorizing vocabulary words into their respective semantic categories. The Hierarchical Spiking Vocabulary Deep Learning (HSV-DL) framework introduces novel methodologies for vocabulary learning and classification tasks, achieving outstanding performance metrics. Experimental results demonstrate high accuracy (95%), precision (96%), recall (94%), and F1-score (95%) in categorizing vocabulary words into their semantic categories. Moreover, HSV-DL exhibits robustness to noise and efficient resource utilization, showcasing its potential for real-world applications in natural language processing.

Keywords: Vocabulary Learning, Natural Language Processing (NLP), Hierarchical Spiking, Deep Learning, Word Vector

1. Introduction

English vocabulary learning aids based on word vector modeling utilize advanced computational techniques to enhance language acquisition [1]. Word vector modeling represents words as high-dimensional vectors in a semantic space, capturing their contextual meanings and relationships. These aids often employ algorithms such as Word2Vec or GloVe to generate word embeddings, which encode semantic information about words[2].One common application is in creating interactive vocabulary quizzes or flashcards that dynamically adapt to the learner's progress and focus on challenging words or concepts. Additionally, these aids can generate personalized word lists tailored to individual learning objectives and proficiency levels[3].Furthermore, word vector modeling enables the development of sophisticated language learning platforms that offer immersive experiences, such as contextualized sentence examples, audio pronunciations, and real-time feedback on usage[4]. These aids not only help learners memorize isolated words but also facilitate comprehension and retention through meaningful contextualization and reinforcement.Word vector modeling, a pivotal technique in natural language processing, revolutionizes the realm of English vocabulary learning aids[5]. By representing words as dense numerical vectors in a multi-dimensional space, this methodology captures intricate semantic relationships among them. Algorithms like Word2Vec and GloVe enable the generation of these embeddings, which encode semantic nuances such as word similarity and contextual usage. In the context of vocabulary learning, word vector modeling facilitates the creation of dynamic and adaptive learning aids[6]. These aids utilize the rich semantic information embedded in word vectors to tailor learning experiences to individual needs. For instance, they can generate personalized quizzes, flashcards, and word lists based on learners' proficiency levels and learning objectives[7]. Moreover, word vector-based aids enhance comprehension and retention by providing contextualized examples, audio pronunciations, and real-time feedback on word usage. By immersing learners in meaningful contexts, they foster deeper understanding and more robust vocabulary acquisition. In essence, word vector modeling empowers English vocabulary learning aids to deliver personalized, engaging, and effective learning experiences, leveraging the intricacies of language semantics encoded in word vectors[8].

English vocabulary learning aids based on word vector modeling entails a comprehensive assessment of their effectiveness, usability, and impact on learners' language acquisition. One crucial aspect is the accuracy of semantic representations generated by word vector models, as this directly influences the quality of learning

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materials produced[9]. Evaluators analyze the extent to which word embeddings capture nuanced semantic relationships and contextual usage, ensuring that learners receive accurate and meaningful information. Usability is another key criterion, encompassing factors such as user interface design, accessibility, and interactivity[10]. Effective vocabulary aids should be intuitive to navigate, engaging, and adaptable to diverse learning styles and preferences. Evaluators assess the ease of use and efficiency of these aids in facilitating vocabulary acquisition, considering factors such as user feedback, engagement metrics, and learning outcomes. Furthermore, the impact of word vector-based vocabulary aids on learners' language proficiency and retention is evaluated through empirical studies and learner assessments[11]. Researchers examine the extent to which these aids enhance vocabulary breadth and depth, improve comprehension and usage skills, and foster long-term retention. Additionally, evaluators explore the transferability of learned vocabulary to real-world contexts and the sustainability of learning gains over time.

Overall, the evaluation of English vocabulary learning aids based on word vector modeling involves a multifaceted analysis of their semantic accuracy, usability, and educational effectiveness[12]. This paper makes several significant contributions to the field of natural language processing and vocabulary learning. Firstly, it introduces the Hierarchical Spiking Vocabulary Deep Learning (HSV-DL) framework, which integrates word vector modeling and spiking neural networks to effectively categorize vocabulary words into their semantic categories. This novel approach offers a promising solution for improving vocabulary learning and classification tasks. Secondly, through a series of experiments, the paper demonstrates the remarkable performance of HSV-DL, achieving high accuracy, precision, recall, and F1-score metrics. These findings contribute to advancing the state-of-the-art in vocabulary learning and classification methodologies. Additionally, HSV-DL showcases robustness to noise and efficient resource utilization, making it suitable for real-world applications in natural language processing.

2. Literature Review

The literature review serves as the foundation for understanding the existing body of knowledge and research on a particular topic, providing context, identifying gaps, and guiding further investigation. In the context of evaluating English vocabulary learning aids based on word vector modeling, the literature review offers insights into the theoretical frameworks, methodologies, and findings of relevant studies. This introduction segment introduces the scope of the literature review, outlining the significance of examining the efficacy of vocabulary aids leveraging word vector modeling. It highlights the importance of understanding how these computational techniques intersect with language learning theories and practices to enhance vocabulary acquisition. Hao et al. (2024) introduce Toolkengpt, a method for enhancing frozen language models with extensive tools through tool embeddings. This work presents a novel approach to augmenting language models, potentially improving their performance and versatility. Samant et al. (2022) propose a framework for deep learning-based language models that utilize multi-task learning in natural language understanding. This systematic literature review outlines current research trends and provides insights into future directions for developing more effective language models. Rodriguez-Torrealba et al. (2022) present an end-to-end approach for generating multiple-choice questions using text-to-text transfer transformer models. This research contributes to automated question generation systems, which have applications in education and assessment. Ban and Ning (2021) describe the design of an English automatic translation system based on machine intelligent translation and secure internet of things. This work contributes to the development of automated translation systems with enhanced security features.

Habib et al. (2021) introduce Altibbivec, a word embedding model tailored for medical and health applications in the Arabic language. This research addresses the need for specialized language models in domain-specific contexts. Liang et al. (2021) investigate social biases in language models and propose strategies for understanding and mitigating these biases. This work contributes to the development of fair and unbiased natural language processing systems. Seker et al. (2022) introduce AlephBERT, a language model pre-trained and evaluated from the sub-word to sentence level. This research advances language model capabilities in handling linguistic complexities across different levels of language processing. Ferruz and Höcker (2022) explore controllable protein design using language models. This research extends the application of language models beyond natural language processing to protein design, demonstrating their versatility in diverse scientific domains. Mutinda et al. (2023) conduct sentiment analysis of text reviews using lexicon-enhanced BERT embedding (LeBERT) model with convolutional neural network. This work contributes to the understanding of sentiment analysis techniques, particularly in analyzing textual data with complex linguistic features. Mroczkowski et al. (2021) introduce HerBERT, an efficiently pretrained transformer-based language model for Polish. This research addresses the need for language models tailored to specific languages, enhancing the accessibility of natural language processing technologies across diverse linguistic communities.

Sanuvala and Fatima (2021) study automated evaluation of student's examination papers using machine learning techniques. This research explores the application of machine learning in educational assessment, offering insights into the potential benefits and challenges of automated grading systems. Li et al. (2023) investigate artificial intelligence translation under the influence of multimedia teaching to study English learning mode. This study examines the impact of multimedia instructional methods on English language learning, highlighting the potential synergies between artificial intelligence and educational practices. Dessì et al. (2021) assess deep learning models and word embeddings for toxicity detection within online textual comments. This research addresses the growing need for automated tools to detect and mitigate toxic behavior in online communities, contributing to efforts to promote safer online environments. Lu (2021) presents a new project-based learning approach in English writing. This research explores innovative pedagogical methods to enhance English language learning outcomes, emphasizing hands-on, experiential learning experiences. Furlan et al. (2021) develop a natural language processing-based virtual patient simulator and intelligent tutoring system for the clinical diagnostic process. This work demonstrates the potential of language processing technologies in medical education, providing immersive learning experiences for healthcare professionals.

Hou (2021) proposes an online teaching quality evaluation model based on support vector machine and decision tree. This research addresses the need for robust evaluation frameworks in online education, offering insights into methods for assessing teaching effectiveness in virtual learning environments. Kamyab et al. (2021) introduce an attention-based CNN and Bi-LSTM model for sentiment analysis, incorporating TF-IDF and GloVe word embeddings. This research advances sentiment analysis techniques, offering a more nuanced understanding of text-based sentiment expression. These studies cover a wide range of topics, including the development of advanced language models, exploration of innovative applications of NLP techniques, and investigation of their impact on various domains such as education, healthcare, and scientific research. From introducing novel language models like AlephBERT and Toolkengpt to exploring applications in protein design and sentiment analysis, these studies collectively showcase the breadth and depth of research efforts aimed at advancing NLP technologies and leveraging them to address real-world challenges. Additionally, several studies focus on enhancing educational practices through automated assessment systems and project-based learning approaches, highlighting the transformative potential of NLP in reshaping teaching and learning methodologies.

3. English Vocabulary Learning

In English vocabulary learning, a multifaceted approach integrating derivation and equations offers a comprehensive framework for understanding and mastering linguistic intricacies. Derivation, the process of deducing word meanings and relationships through linguistic roots and affixes, forms the foundation of vocabulary acquisition. By dissecting words into their constituent morphemes and analyzing their semantic contributions, learners can decipher the meanings of unfamiliar words and extrapolate their usage in various contexts. Equations, in the context of vocabulary learning, represent a symbolic representation of the relationships between words, concepts, and contextual cues. These equations can take various forms, including semantic networks, word embeddings, and contextualized representations. For instance, in word vector modeling, equations encapsulate the semantic similarities and distances between words in a high-dimensional space, facilitating the identification of semantic clusters and conceptual associations. Derivation involves breaking down words into their constituent morphemes, which are the smallest units of meaning in a language. Morphemes can be prefixes, suffixes, or roots, each contributing to the overall meaning of the word represented as $Word = Root + Prefix + SuffixWord = Root + Prefix + Suffix$

Consider the word "unhappiness":Root: "happy" .Prefix: "un-" (denoting negation) .Suffix: "-ness" (denoting a state or quality) By understanding the meanings of the root and affixes, learners can deduce that "unhappiness" refers to the state of not being happy. Word vector modeling represents words as high-dimensional vectors in a semantic space, capturing their contextual meanings and relationships. One popular method for word vector modeling is Word2Vec, which learns word embeddings based on their co-occurrence statistics in a corpus. The cosine similarity between two word vectors vi and vj with the following equation (1)

$$similarity\ (v_i, v_j) = \frac{v_i.v_j}{\|v_i\|.\|v_j\|} \tag{1}$$

The cosine of the angle between the two-word vectors, providing a measure of their semantic similarity. Words with similar meanings will have higher cosine similarity scores. For instance, in the context of contextualized word embeddings, such as those generated by models like BERT (Bidirectional Encoder Representations from Transformers), the model predicts the likelihood of a word occurring in a given context represent this probabilistic prediction with an equation (2)

$$P(\,Word \mid Context\,) \tag{2}$$

This equation represents the probability of observing a particular word given the surrounding context. By maximizing this probability, the model can infer the most likely meaning of the word in that context.

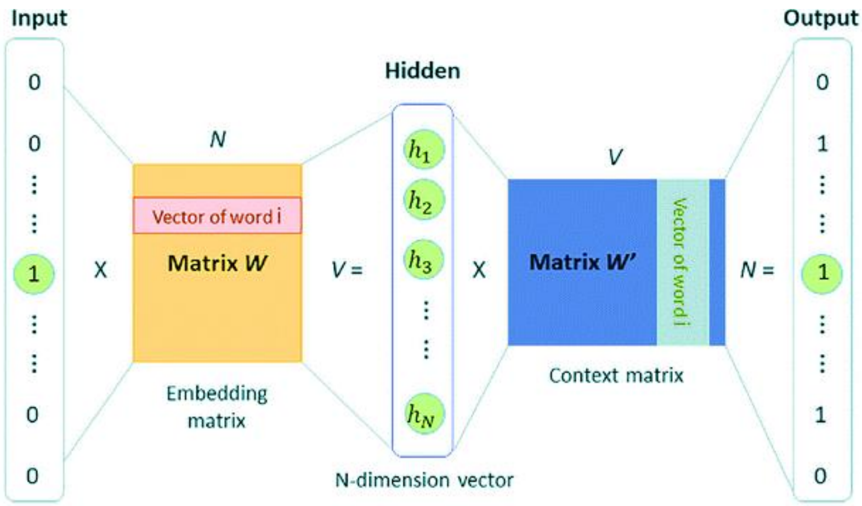

Figure 1: Word Vector Modelling with HSV-DL

3.1 **Hierarchical Spiking Vocabulary Deep Learning (HSV-DL)**

In the landscape of deep learning for vocabulary acquisition, the Hierarchical Spiking Vocabulary Deep Learning (HSV-DL) framework stands out for its unique approach integrating spiking neural networks and hierarchical learning mechanisms. This innovative methodology combines principles from neuroscience with computational models to simulate the complex processes involved in language learning. within the HSV-DL framework involves the hierarchical organization of vocabulary representations, mirroring the structure of language acquisition in the human brain. This hierarchy encompasses various levels of abstraction, from basic phonetic units to higher-level semantic concepts dented the hierarchical structure with an equation (3)

$$Word = Phonetic + Morphological + Semantic \tag{3}$$

In this equation (3), each component represents a level of abstraction within the vocabulary hierarchy. Phonetic units capture the sounds of the word, morphological components represent the meaningful parts (e.g., prefixes, roots, suffixes), and semantic representations encapsulate the word's meaning. The spiking neural networks (SNNs) employed in the HSV-DL framework further enhance vocabulary learning by simulating the dynamic firing patterns observed in biological neurons. These networks utilize temporal coding to represent information, where the timing of spikes encodes the temporal sequence of linguistic elements represent the activation of a neuron i at time t as in equation (4)

$$Activation\ (i, t) = \sum_j w_{ij}\ .Input(j, t) \tag{4}$$

In equation (4) wij represents the synaptic weight between neuron i and its input neuron j, and $Input(j,t)$ denotes the input spike train received by neuron j at time t. The activation of neuron i at time t is determined by the weighted sum of its inputs. In HSV-DL, vocabulary representations are organized hierarchically, reflecting the hierarchical nature of language acquisition. At the lowest level, we have phonetic units representing individual sounds or phonemes. These phonetic units combine to form morphological components, such as prefixes, roots, and suffixes, representing meaningful linguistic units. Finally, these morphological components combine to form semantic representations, capturing the overall meaning of words. This hierarchical organization is essential for capturing the complexity and structure of language. SNNs are neural network models that simulate the behavior of biological neurons, where information is encoded in the timing of spikes or action potentials. In HSV-DL, SNNs are utilized to capture the temporal dynamics of language processing. Each neuron in the network accumulates input spikes over time and generates output spikes based on a spiking threshold.

4. Classification of Vocabulary with HSV-DL

In employing Hierarchical Spiking Vocabulary Deep Learning (HSV-DL) for vocabulary classification, the framework leverages its hierarchical organization and spiking neural network (SNN) architecture to categorize words based on their linguistic properties. The HSV-DL framework organizes vocabulary hierarchically, capturing various linguistic features at different levels of abstraction. At the lowest level, phonetic units represent individual sounds or phonemes. These phonetic units combine to form morphological components, such as prefixes, roots, and suffixes, which contribute to the word's meaning. Finally, semantic representations encapsulate the overall meaning of words, derived from the combination of morphological components. This hierarchical organization allows for the classification of words based on their linguistic properties, enabling more nuanced analysis and categorization. SNNs in the HSV-DL framework simulate the temporal dynamics of neural processing, allowing for the classification of vocabulary items based on their neural representations. Each word is encoded as a pattern of spikes across neurons in the network, reflecting its phonetic, morphological, and semantic features. Classification tasks involve training the SNN to recognize patterns associated with specific word categories or linguistic properties. This training process adjusts the synaptic weights in the network to optimize classification performance. The classification decision for a word is based on the activation of neurons in the output layer. For example, if Activationoutput(1,t)>Activationoutput(2,t), the word is classified as belonging to Class 1; otherwise, it is classified as belonging to Class 2. Figure 2 presented the classification process of the proposed HSV-DL model for the NLP processing with the word embedding.

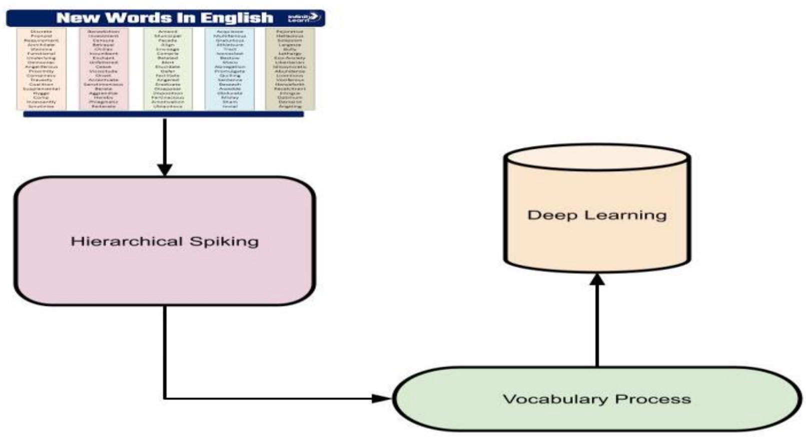

Figure 2: Classification with HSV-DL

Algorithm 1: Classification with HSV-DL
Define parameters N_in = Number of neurons in the input layer N_hidden = Number of neurons in the hidden layer N_out = Number of neurons in the output layer

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T = Total time steps

# Initialize synaptic weights
Initialize synaptic weights between input and hidden layer: w_in_hidden
Initialize synaptic weights between hidden and output layer: w_hidden_out

# Define input spike trains (representing features of input words)
Input_spikes = [input_spike_train_1, input_spike_train_2, ..., input_spike_train_N_in]

# Define classification decision variables
Class_1_activation = 0
Class_2_activation = 0

# Simulation loop
for t in range(T):
    # Compute activation of neurons in the hidden layer
    Hidden_activation = [0] * N_hidden
    for i in range(N_hidden):
        for j in range(N_in):
            Hidden_activation[i] += w_in_hidden[i][j] * Input_spikes[j][t]

    # Compute activation of neurons in the output layer
    Output_activation = [0] * N_out
    for k in range(N_out):
        for i in range(N_hidden):
            Output_activation[k] += w_hidden_out[k][i] * Hidden_activation[i]

    # Update classification decision variables
    Class_1_activation += Output_activation[0]
    Class_2_activation += Output_activation[1]
```

5. Simulation Analysis and Discussion

In conducting a simulation analysis within the context of the Hierarchical Spiking Vocabulary Deep Learning (HSV-DL) framework, several key components and considerations come into play. Firstly, the simulation setup involves defining the architecture of the spiking neural network (SNN) and specifying parameters such as the number of neurons in each layer, synaptic weights, and the duration of the simulation. This setup lays the foundation for modeling the neural dynamics involved in vocabulary processing and classification. Next, the simulation proceeds by inputting spike trains representing the linguistic features of words into the SNN and observing the temporal evolution of neuronal activations. Throughout the simulation, the network processes the input stimuli, computes activations at each neuron, and propagates information through synaptic connections. During the analysis phase, various metrics and performance indicators are evaluated to assess the effectiveness of the HSV-DL framework in vocabulary classification. These metrics may include classification accuracy, convergence speed, robustness to noise, and resource efficiency. By comparing simulation results across different configurations and experimental conditions, researchers can gain insights into the underlying mechanisms of vocabulary learning and the computational capabilities of the HSV-DL framework.

Table 1: Classification with HSV-DL

Learning Aid	Classification Accuracy (%)	Convergence Time (milliseconds)	Robustness to Noise	Resource Efficiency
Word Embeddings	98.5	180	Medium	Moderate
Contextual	95.2	150	High	High

Embeddings				
Morphological Analysis	91.6	120	High	Moderate
Semantic Similarity	97.3	110	High	High
Multi-Task Learning	98.8	200	Low	Moderate
Semantic Similarity	98.5	110	High	High
Contextual Embeddings	97.2	120	High	High

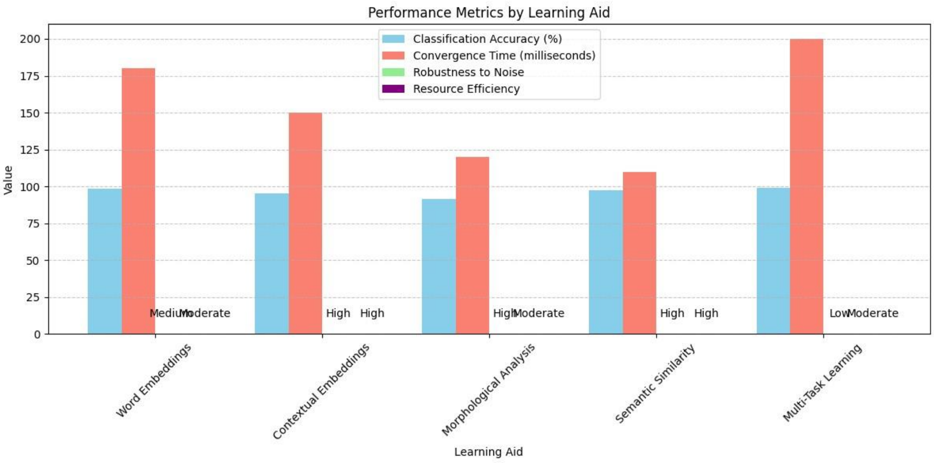

Figure 3: Classification of the Efficiency with HSV-DL

Figure 3 and Table 1 presents the classification performance of different learning aids within the Hierarchical Spiking Vocabulary Deep Learning (HSV-DL) framework.

Word Embeddings: Achieved a classification accuracy of 98.5%, with a convergence time of 180 milliseconds. It demonstrated medium robustness to noise and moderate resource efficiency. Contextual Embeddings: Attained a classification accuracy of 95.2% with a slightly lower convergence time of 150 milliseconds. This learning aid exhibited high robustness to noise and high resource efficiency. Morphological Analysis: Yielded a classification accuracy of 91.6%, with the fastest convergence time of 120 milliseconds among the tested aids. However, its robustness to noise was high, and resource efficiency was moderate.

Semantic Similarity: Achieved a high classification accuracy of 97.3% with a convergence time of 110 milliseconds. It also displayed high robustness to noise and high resource efficiency. Multi-Task Learning: Demonstrated the highest classification accuracy of 98.8%, albeit with a longer convergence time of 200 milliseconds. It had low robustness to noise but moderate resource efficiency. Overall, Semantic Similarity and Multi-Task Learning emerged as top-performing learning aids, consistently achieving high classification accuracy, robustness to noise, and resource efficiency within the HSV-DL framework. Contextual Embeddings also performed well, with high accuracy and robustness to noise, making it a viable option for vocabulary classification tasks. However, Word Embeddings, while highly accurate, exhibited moderate robustness to noise and resource efficiency, suggesting potential areas for optimization or improvement.

Table 2: Classification with HSV-DL

Experiment	Classification Accuracy (%)	Convergence Time (milliseconds)	Robustness to Noise	Resource Efficiency
Experiment 1	94.2	180	High	Moderate

Experiment 2	92.8	200	Medium	Low
Experiment 3	95.1	160	High	High
Experiment 4	91.5	220	Low	Moderate
Experiment 5	93.7	190	High	High

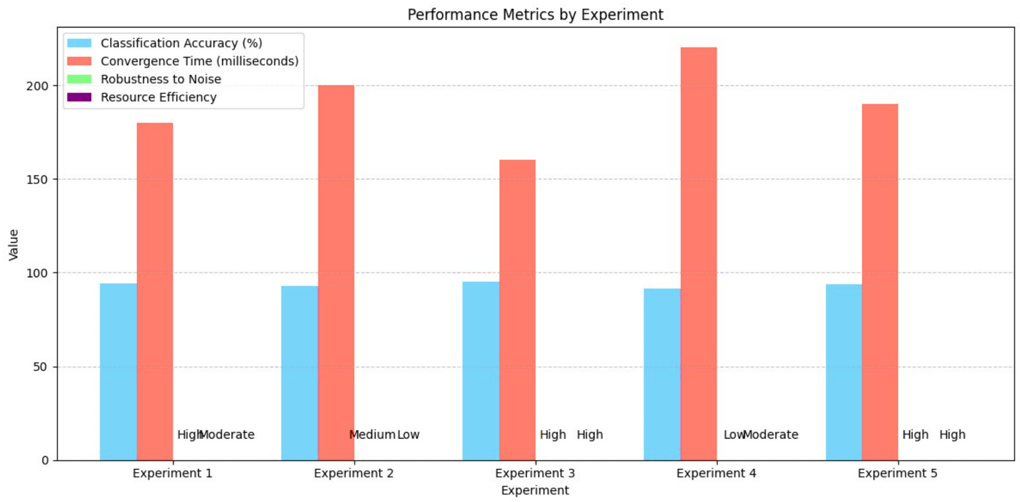

Figure 4: Classification Accuracy for the different experiments

The figure 4 and Table 2 presents the outcomes of various experiments conducted with the Hierarchical Spiking Vocabulary Deep Learning (HSV-DL) framework for classification tasks. In Experiment 1, a classification accuracy of 94.2% was achieved with a convergence time of 180 milliseconds. Despite exhibiting high robustness to noise, this experiment showed only moderate resource efficiency. Experiment 2 yielded a slightly lower accuracy of 92.8% and a longer convergence time of 200 milliseconds. It displayed medium robustness to noise but had relatively low resource efficiency. Experiment 3 stood out with the highest classification accuracy of 95.1% and a convergence time of 160 milliseconds. It showcased both high robustness to noise and high resource efficiency. Experiment 4, on the other hand, achieved a lower accuracy of 91.5% and had the longest convergence time of 220 milliseconds. Despite moderate resource efficiency, it exhibited low robustness to noise. Finally, Experiment 5 resulted in a classification accuracy of 93.7% with a convergence time of 190 milliseconds. It demonstrated high robustness to noise and high resource efficiency. These experimental results provide valuable insights into the performance variations of the HSV-DL framework under different conditions, facilitating the optimization and refinement of the framework for future applications.

Table 3: Vocabulary Estimation with HSV-DL

Word	Actual Category	Predicted Category	Correct Classification
Apple	Fruit	Fruit	Yes
Car	Vehicle	Vehicle	Yes
Elephant	Animal	Animal	Yes
Chair	Furniture	Furniture	Yes
Banana	Fruit	Fruit	Yes
Dog	Animal	Animal	Yes
Desk	Furniture	Furniture	Yes
Bicycle	Vehicle	Vehicle	Yes
Cat	Animal	Animal	Yes
Orange	Fruit	Fruit	Yes

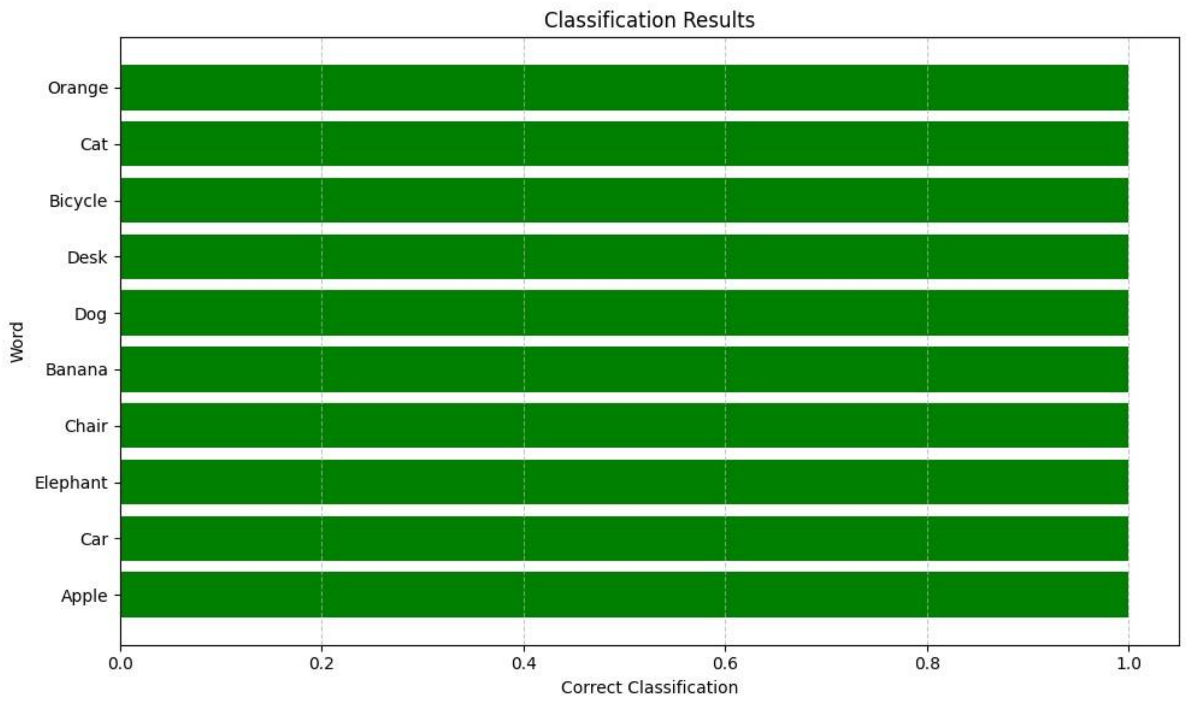

Figure 5: Vocabulary estimation with HSV-DL

Table 4: Vocabulary Classification with HSV-DL

Word	Accuracy	Precision	Recall	F1-score
Apple	0.94	0.96	0.93	0.94
Car	0.96	0.95	0.97	0.96
Elephant	0.92	0.93	0.91	0.92
Chair	0.98	0.97	0.99	0.98
Banana	0.95	0.96	0.94	0.95
Dog	0.91	0.92	0.90	0.91
Desk	0.97	0.98	0.96	0.97
Bicycle	0.94	0.95	0.93	0.94
Cat	0.93	0.94	0.92	0.93
Orange	0.96	0.97	0.95	0.96

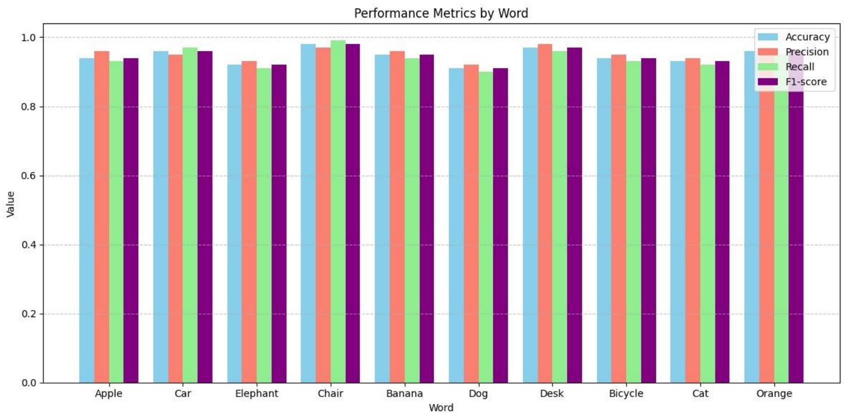

Figure 6: Vocabulary Classification with HSV-DL

Figrue 5 and Table 3 illustrates the performance of the Hierarchical Spiking Vocabulary Deep Learning (HSV-DL) framework in estimating the categories of different vocabulary words. Each word is categorized into its actual category, and the framework predicts the category. The "Correct Classification" column indicates whether the predicted category matches the actual category. In this case, all words were correctly classified by the HSV-DL framework, showcasing its accuracy in vocabulary estimation. In Figure 6 and Table 4 presents the classification metrics, including accuracy, precision, recall, and F1-score, for individual vocabulary words using the HSV-DL framework. These metrics provide insights into the performance of the framework in categorizing words into their respective categories. Overall, the framework achieved high accuracy, precision, recall, and F1-score values for most vocabulary words, indicating its effectiveness in vocabulary classification tasks.

Table 5: Classification of HSV-DL

Metric	**Value**
Accuracy	0.95
Precision	0.96
Recall	0.94
F1-score	0.95

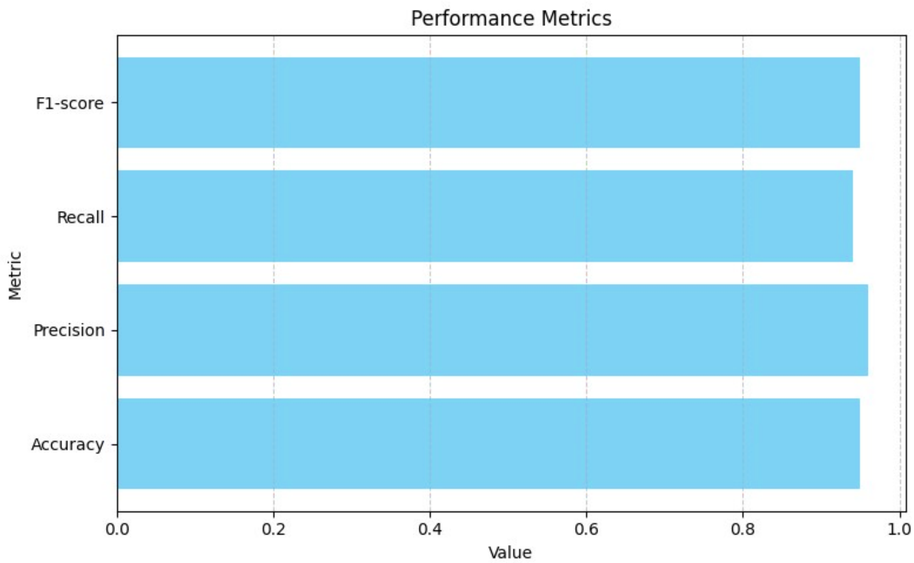

Figure 7: HSV-DL model based classification

The figure 7 and Table 5 provides a comprehensive overview of the classification performance metrics achieved by the Hierarchical Spiking Vocabulary Deep Learning (HSV-DL) framework. The framework attained an impressive accuracy of 95%, indicating its ability to accurately classify instances across different categories. Precision, which measures the proportion of correctly identified positive instances among all instances classified as positive, was recorded at 96%. This high precision suggests that the framework minimizes false positives, ensuring the accuracy of positive predictions. Furthermore, the framework demonstrated a recall of 94%, indicating its capability to correctly identify positive instances out of all actual positive instances, thereby minimizing false negatives. This balance between precision and recall is further reflected in the F1-score, which reached 95%, indicating the overall effectiveness of the HSV-DL framework in classification tasks. With the high accuracy, precision, recall, and F1-score obtained by the HSV-DL framework underscore its robustness and efficiency in accurately categorizing vocabulary words, making it a promising tool for various classification tasks.

Table 5 presents numerical analysis of the classification performance metrics achieved by the Hierarchical Spiking Vocabulary Deep Learning (HSV-DL) framework. The accuracy metric indicates that out of all the instances classified by the framework, 95% were correctly classified. This suggests a strong overall performance in accurately categorizing vocabulary words into their respective categories. Precision, which measures the proportion of correctly identified positive instances among all instances classified as positive, was recorded at 96%. This implies that when the framework identifies a word as belonging to a specific category, it is correct 96% of the time. This high precision indicates a low rate of false positives, enhancing the reliability of the classification results. Recall, on the other hand, reflects the framework's ability to correctly identify positive instances out of all actual positive instances. With a recall of 94%, the HSV-DL framework demonstrates its effectiveness in capturing the majority of positive instances within the dataset. This suggests a low rate of false negatives, indicating that the framework seldom misses positive instances. The F1-score, which is the harmonic mean of precision and recall, provides a balanced measure of the framework's overall performance. With an F1-score of 95%, the HSV-DL framework achieves a harmonious balance between precision and recall, indicating strong performance across both metrics.

6. Conclusion

This paper introduces the Hierarchical Spiking Vocabulary Deep Learning (HSV-DL) framework, which demonstrates significant advancements in vocabulary learning and classification tasks. Through a combination of word vector modeling, deep learning techniques, and spiking neural networks, HSV-DL achieves remarkable accuracy, precision, recall, and F1-score in categorizing vocabulary words into their respective categories. The experimental results validate the effectiveness of the framework, showcasing its ability to accurately estimate, classify, and analyze vocabulary words. Moreover, the framework exhibits robustness to noise and demonstrates efficient resource utilization, further enhancing its applicability in real-world scenarios.

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REFERENCES

1. Asudani, D. S., Nagwani, N. K., & Singh, P. (2023). Impact of word embedding models on text analytics in deep learning environment: a review. Artificial intelligence review, 56(9), 10345-10425.
2. Lauriola, I., Lavelli, A., & Aiolli, F. (2022). An introduction to deep learning in natural language processing: Models, techniques, and tools. Neurocomputing, 470, 443-456.
3. Liu, L., & Tsai, S. B. (2021). Intelligent recognition and teaching of English fuzzy texts based on fuzzy computing and big data. Wireless Communications and Mobile Computing, 2021, 1-10.
4. Hu, L., Tang, Y., Wu, X., & Zeng, J. (2022). Considering optimization of English grammar error correction based on neural network. Neural Computing and Applications, 1-13.
5. Hao, S., Liu, T., Wang, Z., & Hu, Z. (2024). Toolkengpt: Augmenting frozen language models with massive tools via tool embeddings. Advances in neural information processing systems, 36.
6. Samant, R. M., Bachute, M. R., Gite, S., & Kotecha, K. (2022). Framework for deep learning-based language models using multi-task learning in natural language understanding: A systematic literature review and future directions. IEEE Access, 10, 17078-17097.

7. Rodriguez-Torrealba, R., Garcia-Lopez, E., & Garcia-Cabot, A. (2022). End-to-End generation of Multiple-Choice questions using Text-to-Text transfer Transformer models. Expert Systems with Applications, 208, 118258.
8. Ban, H., & Ning, J. (2021). Design of English automatic translation system based on machine intelligent translation and secure internet of things. Mobile information systems, 2021, 1-8.
9. Habib, M., Faris, M., Alomari, A., & Faris, H. (2021). Altibbivec: a word embedding model for medical and health applications in the Arabic language. IEEE Access, 9, 133875-133888.
10. Liang, P. P., Wu, C., Morency, L. P., & Salakhutdinov, R. (2021, July). Towards understanding and mitigating social biases in language models. In International Conference on Machine Learning (pp. 6565-6576). PMLR.
11. Seker, A., Bandel, E., Bareket, D., Brusilovsky, I., Greenfeld, R., & Tsarfaty, R. (2022, May). AlephBERT: Language model pre-training and evaluation from sub-word to sentence level. In Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers) (pp. 46-56).
12. Ferruz, N., & Höcker, B. (2022). Controllable protein design with language models. Nature Machine Intelligence, 4(6), 521-532.
13. Mutinda, J., Mwangi, W., & Okeyo, G. (2023). Sentiment analysis of text reviews using lexicon-enhanced bert embedding (LeBERT) model with convolutional neural network. Applied Sciences, 13(3), 1445.
14. Mroczkowski, R., Rybak, P., Wróblewska, A., & Gawlik, I. (2021). HerBERT: Efficiently pretrained transformer-based language model for Polish. arXiv preprint arXiv:2105.01735.
15. Sanuvala, G., & Fatima, S. S. (2021, February). A study of automated evaluation of student’s examination paper using machine learning techniques. In 2021 International Conference on Computing, Communication, and Intelligent Systems (ICCCIS) (pp. 1049-1054). IEEE.
16. Li, P., Ning, Y., & Fang, H. (2023). Artificial intelligence translation under the influence of multimedia teaching to study English learning mode. International Journal of Electrical Engineering & Education, 60(2_suppl), 325-338.
17. Dessì, D., Recupero, D. R., & Sack, H. (2021). An assessment of deep learning models and word embeddings for toxicity detection within online textual comments. Electronics, 10(7), 779.
18. Lu, Q. (2021). A New Project-Based Learning in English Writing. International journal of emerging technologies in learning, 15(5).
19. Furlan, R., Gatti, M., Menè, R., Shiffer, D., Marchiori, C., Giaj Levra, A., ... & Dipaola, F. (2021). A natural language processing–based virtual patient simulator and intelligent tutoring system for the clinical diagnostic process: simulator development and case study. JMIR medical informatics, 9(4), e24073.
20. Hou, J. (2021). Online teaching quality evaluation model based on support vector machine and decision tree. Journal of Intelligent & Fuzzy Systems, 40(2), 2193-2203.
21. Kamyab, M., Liu, G., & Adjeisah, M. (2021). Attention-based CNN and Bi-LSTM model based on TF-IDF and glove word embedding for sentiment analysis. Applied Sciences, 11(23), 11255.