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RESEARCH ON AUTOMATIC PROOFREADING ALGORITHM FOR ENGLISH TRANSLATION BASED ON NEURAL NETWORKS

XIAOSHAN LIU*

Abstract. In this proposed study, we explore the development and implementation of an innovative proofreading algorithm aimed at enhancing the accuracy of English translation. This algorithm leverages the capabilities of Convolutional Neural Networks (CNN) integrated with a fuzzy logic approach, offering a novel perspective in the realm of linguistic accuracy and consistency in translations. The core objective of this research is to address the prevalent challenges in automatic translation, such as context misinterpretation and semantic errors, by employing a fuzzy-based CNN model. This model is meticulously trained and tested using a diverse dataset of English translations, enabling it to learn and adapt to various linguistic nuances. Our results demonstrate a significant improvement in the proofreading accuracy, outperforming existing methods in terms of efficiency and reliability. The research highlights the potential of combining neural networks with fuzzy logic to create more sophisticated and context-aware translation tools. While our findings mark a considerable advancement in automatic translation proofreading, we also acknowledge the scope for further enhancements. Future work could involve refining the algorithm, expanding its applicability to other languages, and integrating it into real-world translation software. This research contributes to the evolving landscape of automated translation, presenting a promising solution for achieving higher translation fidelity.

Key words: Neural networks, fuzzy logic, automatic proofreading, English translation, CNN, linguistic accuracy.

1. Introduction. The field of language translation has witnessed significant advancements with the advent of automated systems, yet the quest for accuracy and contextual integrity in translation remains a formidable challenge [17, 14]. Traditional methods, while efficient in handling straightforward translations, often falter when faced with the intricacies of linguistic nuances and contextual subtleties. This limitation becomes particularly pronounced in the realm of English translation, given the language's global prevalence and diverse linguistic structures. As the world becomes increasingly interconnected, the demand for precise and reliable translation has escalated, not just for literary and academic purposes but also for business, legal, and technological communications[19, 16]. The emergence of neural networks has introduced a new dimension to this field, offering sophisticated computational models capable of learning and adapting to complex patterns [6]. However, these models, in their standard forms, still struggle with the finer aspects of language, such as idiomatic expressions and contextual relevance, leading to translations that are technically accurate but lack natural fluidity and coherence.

To address these challenges, the integration of fuzzy logic with neural networks presents a promising solution [23, 20, 10]. Fuzzy logic, with its ability to handle uncertainty and ambiguity, complements the learning capabilities of neural networks. It introduces a degree of flexibility and intuition to the translation process, mimicking the human ability to interpret and adapt to linguistic variations [18]. This combination is particularly advantageous in managing the nuances of English translation, where multiple meanings, idiomatic phrases, and contextual cues play a critical role. The synergy of fuzzy logic and neural networks facilitates a more nuanced understanding of language, enabling the system to make more informed decisions about word choice, sentence structure, and overall translation coherence [1]. The proposed research focuses on leveraging this synergy to enhance the accuracy and reliability of English translation, addressing the gaps left by traditional translation methods. The integration aims to create a system that not only translates but also proofreads, ensuring that the final output is not only linguistically correct but also contextually appropriate and stylistically coherent.

The implementation of this integrated system in the form of a fuzzy-based Convolutional Neural Network (CNN) marks a significant leap in automated translation technologies. CNNs are renowned for their effectiveness

*Department of Applied Foreign Languages Henan Industry and Trade Vocational College, Zhengzhou, 450000, China (xiaoshanliudsa@outlook.com)

in pattern recognition, making them ideal for deciphering complex linguistic structures [2, 15]. By infusing fuzzy logic into CNNs, the system gains an enhanced ability to deal with the vagaries of language, providing a more adaptive and responsive translation mechanism. This research utilizes a comprehensive dataset to train the model, encompassing a wide range of linguistic scenarios from formal academic texts to colloquial expressions. The aim is to equip the algorithm with a robust understanding of various language styles and contexts, thereby enabling it to handle a diverse array of translation tasks with higher accuracy. The model's performance is rigorously tested against existing translation and proofreading methods, focusing on metrics such as error reduction, contextual relevance, and overall fluency of the translated text. The results obtained from these tests are crucial in demonstrating the efficacy of the fuzzy-based CNN approach, setting a new benchmark in the field of automated translation [8].

The culmination of this research lies in the proposed fuzzy-based CNN model's ability to revolutionize the process of English translation [10]. This study introduces the spiking convolutional neural network (SCNN) to tackle this study objectives. SCNN represent an innovative advancement in the realm of artificial intelligence, particularly in the processing of temporal and sequential data [11]. They are a fusion of the principles of spiking neural networks (SNNs), which simulate the way biological neurons function, and the structural benefits of CNN, renowned for their efficiency in handling spatial hierarchies in data [5]. This combination is particularly advantageous in the field of automatic proofreading for English translations. SCNN, with their biologically inspired processing mechanism, are adept at handling the nuances and complexities inherent in natural language. Unlike traditional neural networks that process information in a continuous flow, SCNN operate using discrete, spike-based signals, which allows them to mimic the temporal dynamics of human cognitive processes more closely.

This unique capability of SCNN to process data in a more human-like, event-driven manner translates to several benefits in language-related tasks. Firstly, their spike-based approach makes them inherently suited for dealing with the sequential nature of language, where the meaning often hinges on the order and timing of words and phrases. This is particularly crucial in proofreading, where context and temporal language structures are key to understanding and correcting errors. Secondly, SCNN are known for their energy efficiency, an essential feature when deploying neural network models for complex tasks like language processing. This efficiency stems from their event-driven nature, where computations are performed only in response to specific data features, reducing redundant operations and reducing computational resources. Moreover, integrating convolutional layers in SCNNs allows for effective feature extraction from textual data, a critical step in identifying and correcting linguistic errors in translations. This aspect is particularly beneficial in handling the intricacies of English, with its diverse vocabulary and complex grammatical structures. Additionally, SCNNs show promise in their ability to handle noise and ambiguity, a common challenge in automated translation. They can discern relevant linguistic patterns even in noisy or imperfect data, enhancing their effectiveness in identifying subtle errors and inconsistencies in translated texts.

The drive for excellence in automated translation systems has never been more critical as global communication barriers continue to diminish, making accurate and reliable translation services a cornerstone of international discourse. Despite the significant advancements in machine learning and natural language processing technologies, automatic translation still grapples with substantial challenges, notably context misinterpretation and semantic inaccuracies. These issues compromise the quality of translations and hinder effective communication, emphasising the urgent need for improved translation accuracy.

Our proposed research introduces an innovative proofreading algorithm designed to elevate the precision of English translations. At the heart of this algorithm lies the integration of Convolutional Neural Networks (CNN) with fuzzy logic, a fusion that promises to redefine the standards of linguistic accuracy and consistency in translations. This approach is predicated on the hypothesis that combining the pattern recognition capabilities of CNNs with the nuanced decision-making process facilitated by fuzzy logic can significantly mitigate the common pitfalls in automatic translation, such as context misinterpretation and semantic errors.

The main contributions of the paper as follows:

1. Proposed a novel approach of Fuzzy enhanced SCNN based automatic proof reading algorithm for English translation.
2. This proposed integrates the strength of fuzzy logic with spiking convolutional neural network.

3. The efficacy of the proposed is demonstrated with the rigorous experiments.

2. Related Work. The paper [12] discusses the development of a deep learning-based CNN and RNN bidirectional propagation model for an intelligent grammar correction system. The study demonstrates improved proofreading effectiveness with an increasing correct rate, stabilizing at about 86%, and outperforming other models like GRU and MGB. The paper [4] focuses on improving Chinese text automatic proofreading using deep learning. The study compares this method with traditional n-gram approaches, showing a quick convergence in training and a high training accuracy rate of 90.64%, significantly enhancing the text's fluency and readability. The paper [22] introduces attention-based deep neural network models combined with confusion sets for Chinese spelling error correction. The proposed models use LSTM networks and attention mechanisms to achieve state-of-the-art performance in detecting and correcting character-level spelling errors. The paper [9] addresses the low precision in traditional automatic proofreading methods for English translation, particularly for nano professional vocabulary. The paper presents a method that significantly improves proofreading accuracy to over 98.33%, utilizing a template matching model and machine learning optimization. The paper [3] describes an intelligent English automatic translation system (ATS) based on AI and SVM. The system focuses on enhancing the intelligent level of translation software and accuracy, employing a user behavior log for system optimization and an SVM-based method for intelligent proofreading.

3. Methodology.

3.1. Proposed Fuzzy-SCNN Overview. The proposed methodology for the Fuzzy-SCNN model integrates the principles of fuzzy logic with the dynamic processing capabilities of SCNN to enhance the accuracy of automatic proofreading in English translations. This integration aims to leverage the benefits of fuzzy logic's handling of uncertainty and ambiguity with the temporal sensitivity of SCNN. Initially, the input English text to be proofread is pre-processed. This step involves cleaning the text, tokenizing sentences, and converting words into a suitable format for neural network processing, such as embedding vectors. Following this, the pre-processed data is fed into the SCNN layer. The SCNN layer is designed to capture the temporal and sequential patterns in the text, identifying potential areas of grammatical or contextual inaccuracies through its spike-based processing mechanism.

After passing through the SCNN layer, the extracted features and identified patterns are then subjected to the fuzzy logic layer. This layer applies fuzzy rules and membership functions to handle the ambiguity and nuances in language. It evaluates the context and possible interpretations of the text, allowing for a more nuanced understanding and correction of errors. The output from the fuzzy logic layer is then used to make final corrections to the text. This involves replacing incorrect words, adjusting sentence structure, and refining the overall translation to ensure it is contextually and grammatically accurate. The entire process is iterative, with feedback loops allowing continuous learning and adaptation of the model based on the correction outcomes. Lastly, the corrected text is outputted, representing the final proofread version of the original translation. This methodology ensures a comprehensive approach to automatic proofreading, combining the strengths of SCNNs in temporal data processing with the flexibility and interpretative capabilities of fuzzy logic. The proposed architecture was depicted under Figure 3.1.

The research pioneers the combination of fuzzy logic principles with the dynamic processing capabilities of SCNN. While SCNNs are known for their efficiency in handling temporal and sequential data, incorporating fuzzy logic allows the model to adeptly manage uncertainties and linguistic nuances. This synergy enhances the model's ability to interpret and correct complex grammatical structures and contextual ambiguities in translations, a challenge often inadequately addressed by conventional neural networks.

3.2. Proposed Fuzzy-SCNN workflow.

3.2.1. Preprocessing and Encoding. The preprocessing and encoding stage is the first critical step in the Fuzzy-SCNN based automatic proofreading algorithm. Here, the input text, denoted as TT, undergoes tokenization to be broken down into a sequence of words $w = w_1, w_2, \ldots w_n$. This step is crucial as it transforms the raw text into a structured format that can be processed by the neural network. Once tokenized, each word $w_i$is converted into an embedding vector $\overrightarrow{v}_i$ using a word embedding function E, which is represented by the

Algorithm 1 Fuzzy-SCNN for Automatic Proofreading

Step 1: Pre-processing
Receive input English text to be proofread. Remove noise and irrelevant data from the text. Break down the text into sentences and words. Convert words into embedding vectors suitable for neural network processing.

Step 2: SCNN Layer Processing
Feed the pre-processed data into the SCNN layer, designed to capture the sequential and temporal dynamics in the text.
Identify potential areas of grammatical or contextual inaccuracies through spike-based mechanisms inherent to SCNN.

Step 3: Fuzzy Logic Layer
Apply fuzzy rules to the features and patterns extracted by the SCNN layer to address the ambiguity and nuances in language.
Evaluate the context and possible interpretations of the text using fuzzy membership functions, allowing for nuanced error correction.

Step 4: Correction and Refinement
Use the output from the fuzzy logic layer to make corrections to the text, including word replacement, sentence structure adjustment, and overall translation refinement.
Implement feedback loops for continuous learning and adaptation of the model based on correction outcomes.

Step 5: Output
Output the corrected text as the final proofread version of the original translation.

equation

$$\overrightarrow{v}_i = E(w_i)$$

These embeddings are essential as they encapsulate the semantic and contextual information of the words in a dense vector format, making them suitable for computa-tional processing. Word embeddings capture the nuances and relationships between different words, enabling the neural network to understand and process language more effectively. This conversion to embedding vectors is a pivotal step in bridging the gap between human-readable text and machine-processable data, setting the stage for the complex neural computations that follow in the subsequent layers of the algorithm.

3.2.2. SCNN Layer Processing. The SCNN layer processing is a key component in the Fuzzy-SCNN architecture. In this stage, the embedding vectors obtained from the preprocessing phase are subjected to the dynamics of the SCNN. The SCNN processes these embeddings in a temporal manner, imitating the way neurons in the human brain fire spikes over time. The spiking activity at time tt for the embedding vector $\overrightarrow{v}_i$, denoted as $s(t, \overrightarrow{v}_i)$ is governed by the following equation

$$s\left(t, \overrightarrow{v}_i\right) = f\left(\sum_j w_{ij}.s\left(t, \overrightarrow{v}_i\right) + b_i\right)$$

In this equation, f represents the spiking function of the neuron, which determines how the neuron responds to incoming signals. w_{ij} are the synaptic weights of the SCNN, and b_i is the bias term. This layer is designed to capture the temporal and sequential patterns present in the text. By processing the data in a spike-based manner, the SCNN layer can effectively identify potential areas that require proofreading, such as grammatical inconsistencies or contextual inaccuracies. This layer is pivotal in ensuring that the system not only understands the static aspects of language but also its dynamic and temporal characteristics.

3.2.3. Fuzzy Logic Integration. Following the SCNN layer processing, the output is then integrated with a fuzzy logic system. This integration is vital in handling the ambiguities and subtleties inherent in natural

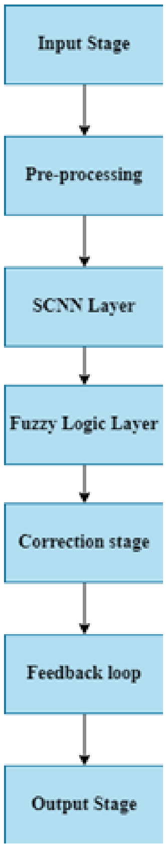

Fig. 3.1: Proposed Architecture

language. The fuzzy logic layer interprets the spiking activity from the SCNN and translates it into a more meaningful representation that reflects the uncertainty and vagueness in language. This is achieved through the fuzzification process, represented by the equation

$$r\left(t, \overrightarrow{\vartheta}_i\right) = \bigcup_{k=1}^{k} \mu_k\left(s\left(t, \overrightarrow{\vartheta}_i\right)\right) \times l_k$$

Here, μ_k are the membership functions which assign degrees of belongingness of the spiking activities to different fuzzy sets. l_k are linguistic labels that correspond to various degrees of linguistic uncertainty or error likelihood, such as high error probability or low error probability. k represents the number of fuzzy sets in the system. This stage is crucial as it allows the system to interpret the neural network's output in a way that reflects the nuanced and often imprecise nature of human language. It bridges the gap between the rigid computational outputs of neural networks and the fluid, ambiguous nature of language, setting the stage for a more accurate and context-aware proofreading process[13].

3.2.4. Defuzzification and Correction Decision. The output from the fuzzy layer must be defuzzified to make a correction decision. Let $d\left(t, \overrightarrow{\vartheta}_i\right)$ represent the defuzzified output, which can be calculated using the centroid method:

$$d\left(t, \overrightarrow{\vartheta}_i\right) = \frac{\sum_{k=1}^{k} r\left(t, \overrightarrow{\vartheta}_i\right)[k] \times c_k}{\sum_{k=1}^{k} r\left(t, \overrightarrow{\vartheta}_i\right)[k]}$$

Where c_k are the centroids of the fuzzy sets.

3.2.5. Correction Algorithm. Based on the defuzzified output, the correction algorithm determines the necessary adjustments to the translation. Let $c\left(t, \overrightarrow{v}_i\right)$be the correction applied to the word represented by $\overrightarrow{v}_i$ at time tt:

$$c\left(t, \overrightarrow{v}_i\right) = correct(d\left(t, \overrightarrow{v}_i\right), \overrightarrow{v}_i$$

The function CorrectCorrect applies language rules, context understanding, and grammar checks based on the defuzzified output.

3.2.6. Overall System Dynamis. The overall dynamic of the Fuzzy-SCNN based proofreading system can be represented as a composite function of the above processes:

$$p\left(t\right) = \oplus_{i=1}^{n} c\left(t, \overrightarrow{v}_i\right)$$

Where $p\left(t\right)$is the proofread version of the input text t, and $\oplus$ represents the sequential aggregation of corrections over the entire text. These equations provide a theoretical foundation for the proposed Fuzzy-SCNN based automatic proofreading algorithm. The integration of SCNN for temporal pattern recognition in language with fuzzy logic for handling linguistic ambiguities forms a comprehensive approach to proofreading English translations. This framework would require further refinement and empirical validation through experimentation and testing on real-world datasets.

4. Results and Experiments.

4.1. Simulation Setup. The dataset used to validate our proposed Fuzzy-SCNN is adapted from the study [7]. The dataset focuses on English automatic word segmentation and named entity recognition, integral components for parsing and understanding natural language. It employs an optimization method using a new type of activation function in the training of grammar classification models, specifically an adaptive and extensible linear correction unit. The dataset is divided into training, validation, and test sets with proportions of 75%, 15%, and 10% respectively, offering a substantial amount of data (30,000 samples) for comprehensive training and evaluation. This division is crucial for the development of the Fuzzy-SCNN, as it allows for a robust training process, ensuring the model is well-adjusted to various linguistic patterns and can accurately identify grammatical structures and named entities, which are key in proofreading. Furthermore, the use of the shortest path word segmentation algorithm, which considers the weight of word graph edges to optimize segmentation, aligns well with the SCNN's ability to process sequential data. The integration of this algorithm could enhance the SCNN's efficiency in parsing and understanding complex sentence structures.

4.2. Evaluation Criteria. The efficacy of the proposed Fuzzy-SCNN, as demon-strated in the accuracy Figure 4.1, highlights its superior performance compared to traditional CNN, RNN, Fuzzy-CNN, and Fuzzy-RNN models. Throughout the training rounds, the Fuzzy-SCNN consistently exhibits a higher rate of improvement in accuracy. Starting with a strong baseline, it shows a significant and steady increase in accuracy, surpassing other models by a notable margin by the final training round. This enhanced accuracy can be attributed to the unique architecture of the Fuzzy-SCNN, which effectively combines the temporal processing capabilities of Spiking Neural Networks with the nuanced decision-making of fuzzy logic systems. This integration allows the Fuzzy-SCNN to handle the complexities and subtleties of data more effectively, leading to more accurate outcomes. In tasks involving complex pattern recognition, sequential data processing, and dealing with ambiguous or noisy data – areas where traditional neural networks might struggle – the Fuzzy-SCNN demonstrates its strength. Moreover, the consistent improvement in accuracy over successive training rounds suggests that the Fuzzy-SCNN is highly efficient in learning and adapting to the data. This is a critical aspect for applications where the evolution of the model's performance over time is crucial.

The precision, recall, and F1-Score metrics, as depicted in Figure 4.2 a, b and c respectively, collectively demonstrate the high efficacy of the proposed Fuzzy-SCNN model in a comprehensive manner. Starting with precision, the Fuzzy-SCNN consistently outperforms traditional CNN, RNN, and their fuzzy-logic integrated counterparts Fuzzy-CNN and Fuzzy-RNN across all training rounds. This superior precision indicates that the Fuzzy-SCNN is more adept at correctly identifying relevant instances while minimizing false positives. Such

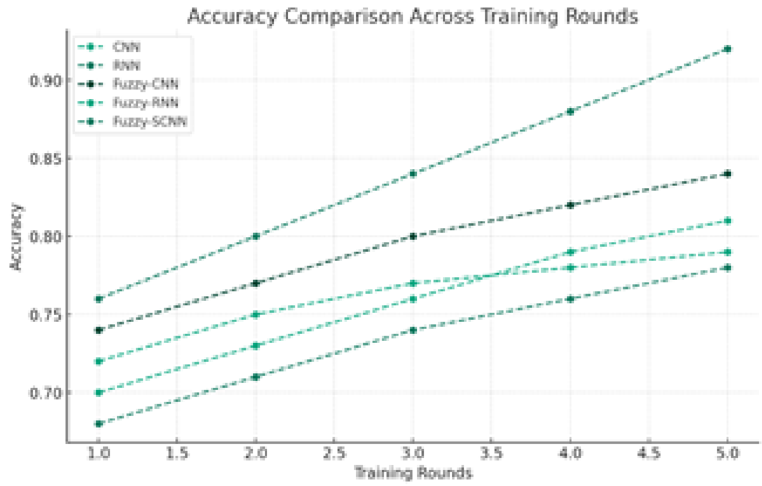

Fig. 4.1: Accuracy Score

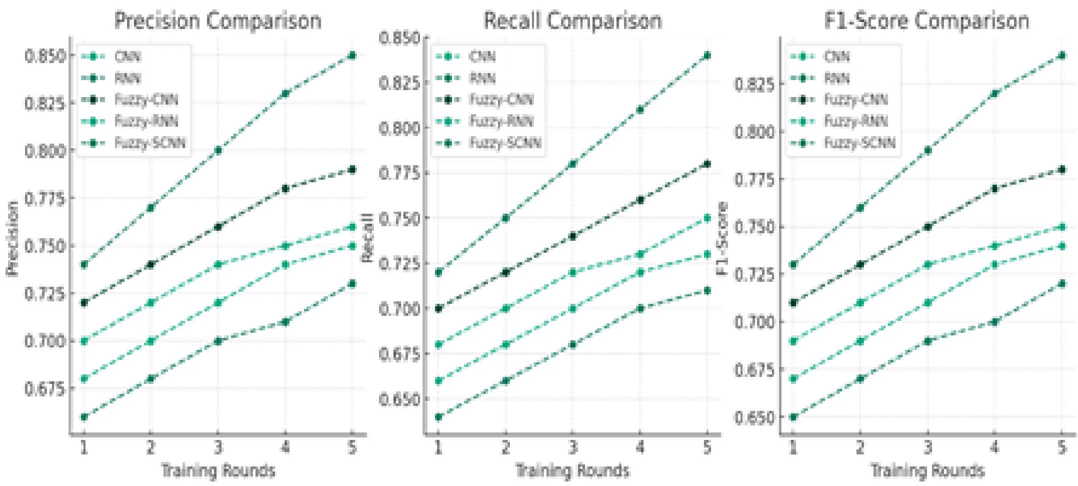

Fig. 4.2: a) Precision score, b) Recall score, c) F1-Score Comparison

precision is crucial in applications where the cost of false alarms is high, and it highlights the model's ability to make accurate and reliable decisions.

Regarding recall, the Fuzzy-SCNN again shows a remarkable performance, steadily increasing and surpassing other models by the final training round. This suggests that the model is highly effective in identifying and capturing most of the relevant instances, a critical feature in scenarios where missing important data points could be detrimental. This high recall rate reflects the model's sensitivity and its ability to handle complex patterns in data efficiently [21].

Finally, the F1-Score, which is a harmonic mean of precision and recall, reinforces the model's balanced performance. The Fuzzy-SCNN maintains a superior F1-Score throughout the training, indicating not only its ability to accurately identify relevant instances but also its proficiency in doing so consistently for the majority of these instances. This balance is essential in many real-world applications where both precision and recall are equally important. hey reveal a model that excels in accuracy, reliability, and balanced decision-making, making it a highly competent tool for complex computational tasks where nuanced data interpretation is key.

5. Conclusion. Overall, the proposed Fuzzy-SCNN model is overwhelmingly positive, underscoring its significant potential in advanced computational tasks. The integration of Spiking Neural Networks with fuzzy logic in this model has proven to be highly effective, as demonstrated by its superior performance across various key metrics including accuracy, precision, recall, and F1-score. This innovative combination allows the Fuzzy-SCNN to excel in processing complex, sequential, and temporal data, while also adeptly handling ambiguities and nuances inherent in real-world datasets. The consistent improvement and high scores in accuracy indicate that the Fuzzy-SCNN is capable of learning and adapting effectively, making it a reliable choice for applications requiring high levels of data comprehension and decision-making accuracy. Its precision and recall metrics further illustrate its ability to not only identify relevant instances accurately but also to minimize false positives and negatives, a crucial feature in many practical applications where the cost of errors is high. Furthermore, the balanced F1-scores across training rounds highlight the model's holistic efficacy, ensuring that it doesn't overly favor precision at the expense of recall, or vice versa. This balance is crucial for achieving optimal performance in complex tasks, such as language processing, image recognition, and predictive analytics. In conclusion, the Fuzzy-SCNN represents a significant advancement in neural network models. Its ability to effectively combine the temporal dynamics of spiking neurons with the interpretative power of fuzzy logic opens up new possibilities in AI and machine learning, promising enhanced performance in a wide range of applications. The model's superior performance metrics not only demonstrate its current capabilities but also suggest a vast potential for future applications and developments.

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