Design of Neural Network-Based Online Teaching Interactive System in the Context of Multimedia-Assisted Teaching

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As the pace of global integration increases, so does the demand for English language courses. Due to the scarcity of English-language learning resources in China, students of the language often need help to improve their spoken English. Advances in artificial intelligence technology and language education approaches have created an entirely novel phase of language teaching and learning. To solve this issue, we can employ deep learning (DL) technology. Speech recognition software is the foundation of verbal communication instruction and is also used as an evaluation tool. More hardware, software, and algorithms are needed to analyze speech signals because of the complexity of speech pronunciation variations, the quantity of speech signal data, a amount of speech characteristics parameters, and the size of speech gratitude and assessment computation. However, it is challenging to increase the precision and speed of conventional speech recognition algorithms since they have run across previously unheard-of bottlenecks. This article focuses on examining the impact of college English multimedia instruction in order to address these issues. The EMLP-SNN technique, which improves multilayer perceptron integration with spiking neural networks, is suggested for identifying oral English pronunciation. The results of the experiments demonstrate that the proposed algorithm has provided an accuracy of 97.5%, which can help students identify discrepancies between their pronunciation and the norm and fix pronunciation mistakes, leading to enhanced oral English learning performance.

Povzetek: Raziskava uvaja EMLP-SNN tehniko za izboljšanje identifikacije angleške izgovorjave s 97,5% točnostjo, kar omogoča študentom izboljšanje učenja govornega angleškega jezika.

1 Introduction

In the realm of multimedia education, there is a growing trend toward the adoption of interactive systems fueled by neural networks. These systems leverage artificial intelligence and machine learning algorithms to create personalized learning experiences, allowing students to progress at their own pace and in a manner that aligns with their individual learning styles [1]. Recent years have witnessed a significant shift towards integrating multimedia into education, with various educational institutions embracing technology to enhance the overall quality of the learning environment. The incorporation of diverse multimedia resources, including movies, animations, and interactive simulations, has proven effective in augmenting student engagement and comprehension of complex subject matter. Despite the manifold benefits associated with multimedia integration, there persist certain challenges that demand attention, such as the need for customized instruction and the difficulty in real-time monitoring of students' academic progress [2]. In this context, the utilization of online educational interactive systems relying on neural networks proves highly advantageous. These systems leverage artificial intelligence and machine learning algorithms to analyze real-time student achievement data. This capability enables dynamic adjustments in the learning experience [3]. For example, if a student encounters difficulties with a specific topic, the system can offer additional resources or modify the lesson's pace to ensure comprehensive understanding. Furthermore, these technologies provide instantaneous feedback on student progress, facilitating a more precise assessment of learning outcomes [4]. The development of a neural network-based interactive online teaching platform is a intricate process spanning various stages. The initial phase involves carefully selecting learning goals and the information to be integrated into the system. Subsequently, the focus shifts to determining the fundamental concepts and skills students need to acquire, along with the selection of multimedia resources for instructing these foundational ideas [5].

The subsequent phase involves crafting the architecture of neural networks designed to scrutinize student achievement data and adapt the learning environment. This intricate task demands an iterative approach, where the selection of appropriate machine learning algorithms and the precise definition of input and output data for the system are paramount [6-8]. Ensuring the neural network's proficiency in accurately analyzing and responding to student actions necessitates extensive training on substantial datasets reflective of students' performance [9]. The subsequent step, which occurs after the structure of the neural network has been created and trained, is to incorporate it into the platform used for online instruction. Developing a user interface that gives students the chance to communicate with the system and obtain individualized feedback and resources is required for this step. Also, the system needs to be able to scale and must be able to manage massive amounts of student data [10-11].

In conclusion, the system has to be assessed to see whether or not it is effective in enhancing the learning outcomes for students. This requires compiling and analyzing data on student performance, after which it is compared to more conventional approaches to teaching. Additionally, the system needs to be continuously updated and enhanced depending on the comments and suggestions made by the instructors and students. The construction of an online teaching interactive system based on neural networks is a complicated process that requires knowledge of artificial intelligence, machine learning, and teaching, helped by multimedia. Yet, these systems can completely transform the way in which children are educated by providing learning experiences that are individualized, interactive, and engaging, as well as that are tuned to the specific requirements of each student. Online teaching interactive systems that are based on neural networks have the potential to alter education and improve the learning results for students all over the world, provided that they continue to be developed and improved upon. Figure 1 represents the overview of speech recognition technology.

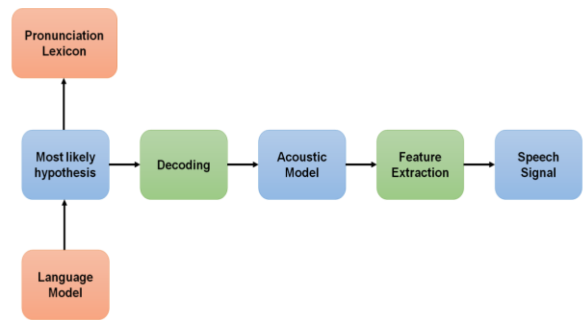

Figure 1: Speech recognition technology.

Following are the paper's main contributions:

- It is suggested to use a multimedia-based impact evaluation strategy for English instruction. It enables students to discern between their pronunciation and that of native speakers, fixes pronunciation blunders, and improves the standard of spoken English learning.
- In order to compensate for the missing features and increase recognition rate, a unique enhanced multilayer perceptron with integrated spiking neural network is proposed in this research.
- Finally, by conducting comparative experiments, this method's superiority is demonstrated.

2 Related work

Table 1: Related works

Reference	Objectives	Findings	Limitations
12	They provided an innovative platform for online intelligent English teaching using deep learning to assist students in becoming more proficient in English in accordance with their levels of knowledge and character development.	The results demonstrated that the system had the potential to increase students' productivity in the classroom and to contextualize their studies.	Limited to essential content, excluding advanced or interactive elements online
13	They constructed artificial and human	According to the results, machine	Limited

	neural networks with the objective of comparing and contrasting their capabilities.	learning systems were recommended to be designed with the ability to provide explanations for their decisions.	interpersonal interaction, hindered practical experiences, varied learning environments impact.
14	To assist teachers in understanding student performance in the classroom, they developed a system with dual capabilities.	The outcomes indicated that DNN could be successfully implemented.	Limited bandwidth, slow access, challenges in real-time engagement, potential disruptions
15	They examined the challenges associated with the present state of education and the constraints of the current system. Those were achieved by integrating an analysis of the current state of teaching and research in both domestic and foreign supplementary education systems, with a focus on computer-based teaching and self-directed English learning facilitated by computer networks.	They utilized a comparative analysis approach to examine the similarities and differences between offline exams written with pencil and paper and online exams taken on a computer and to draw conclusions about the effects of each.	Limited real-time practice, lacks face-to-face communication, hinders immediate feedback
16	They employed "Advanced Multimedia Technology (AMT)" for Teaching Assessment in Engineering Teaching to analyze the current state of advancement in physical education teaching methods.	The results of the experiments showed that the proposed methods could accurately classify student evaluation tasks.	Limited student engagement, tech issues, dependency on internet, distractions
17	They suggested an innovative web-English situational guidance scenario system based on multimedia and sensing.	They evaluate the proposed approach with the existing one. The finding demonstrates the model's reliability.	Latency, bandwidth, congestion affect online teaching interactive network routing efficiency
18	They provided a comprehensive analysis of CALL's evolution and the current state of use, and they made suggestions for how the field could benefit from applying educational model theory to its development and implementation.	An experimental investigation was conducted to evaluate the CAPT system's usefulness, with the results showing that CAPT-adopted classrooms exhibited superior language cognitive abilities.	Tech glitches, limited student engagement, hinder online teaching interactivity.
19	They presented a framework for adaptive learning on mobile devices.	The findings illustrated how their approach handled a variety of learning scenarios generated by students.	Varied technology access, engagement levels hinder online teaching interactivity
20	They developed the foundations of a system based on intelligent human-computer cooperation by analyzing the literature and conducting case studies in artificial intelligence technology and the visual communication design process.	They concluded that the system had a net positive effect on designers and society at large, analyzed the system's future directions, and stated that design was the system's primary mode of human-machine collaboration.	Varied subjects challenge cohesive engagement in online interactive teaching

3 Materials and method

3.1 Enhanced multilayer perceptron integrated spiking neural network (EMLP-SNN)

EMLP-SNN's innovative approach enhances real-time adaptability, facilitating a more dynamic and efficient online learning experience by mimicking the brain's spiking behavior.

The SNN-based topological models receive the returned frame-based features first. These properties are commonly believed to be fixed across the brief optimum point period of segmented frames due to the short temporal length of segmentation frames and the modest variability of speech signals. The highest point-and-fire (IF) neural model with reset by subtract technique is used in this work because it efficiently handles this stationary frame-based data while requiring minimal processing effort. IF neurons, though they do not precisely imitate the complicated temporal dynamics of real neurons, are the ideal choice for applying the neural models utilized in this research, where spike timing has a minimal impact.

The arriving spikes to neuronal *I* at layer *k* are translated into synaptic current by each step s of a discrete-time framework with a total amount of discrete-time steps N_s, as shown below.

$$y_i^k(s) = \sum_j x_{ij}^{k-1}.\theta_j^{k-1}(s) + a_i^k \tag{1}$$

In contrast, θ_i^{k-1}(s) shows that input spikes from input neuron i occurred at time step t. The synaptic weight of the postsynaptic neuron in layer *k-1* is also represented by the x_{ij}^{k-1} and can be thought of in this scenario as a continual injecting current.

According to Equation (2), it shows how Neuronal j converts the input current y_i^k(s) into its potential across the membrane U_i^k(s). Here, a unitary resistance to membranes is assumed without sacrificing generality. Based on the assumption that all synaptic weights are normalized with value to the firing threshold, we set k as the firing threshold for all experiments (see Equation 3), which causes an output spike anytime U_i^k(s) exceeds it.

$$U_i^k(s) = U_i^k(s-1) + y_i^k(s) - \vartheta.\theta_i^k(s-1) \tag{2}$$

$$\theta_i^k(s) = \Theta\left(\mathrm{U}_i^k(s) - \vartheta\right) with \Theta(w) = \begin{cases} 1, \text{if w} \geq 0 \\ 0, \text{otherwise} \end{cases} \tag{3}$$

We can state that the open collective membrane voltage of neuron *i* in layer *k*as follows using equations (1) and (2).

$$U_i^{k,e} = \sum_j x_{ij}^{k-1} \cdot d_j^{k-1} + c_i^k.M_t \tag{4}$$

Where, in accordance with Equation (5), d_j^{k-1} is an input spike frequency from the layer *k* neuron with the highest point-synaptic density.

$$d_j^{k-1} = \sum_{s=1}^{M_t} \theta_j^{k-1}(s) \tag{5}$$

While ignoring their temporal patterns, the U_i^k sums the overall potential at the membrane's contributions of the input pulses from pre-synaptic cells. The tandem architecture for learning section will go into more information about this intermediary quantity, which links the SNN and connected ANN layers for parameter optimization.

A nonlinear function called a multilayer perceptron is created by concatenating different layers of nodes. Either the MLP's input features or the previous layer's output are sent to each layer. The layer's j^{th} node calculates a weighted total of every input as

$$y_{i^k} = \sum_{j=1}^{J} X_{ji}\, xjk + x_i \tag{6}$$

Where X_{ji}andx_i, respectively, stands for the node values and bias, the output of the node is then subjected to the application of a nonlinear function. The sigmoid function related to is the most prevalent.

$$\hat{y}_i = sig(y_i) = \frac{1}{1+\exp(-y_i)} \tag{7}$$

Where for simplicity's sake, the structure's index l was eliminated. An arbitrary number of layers can be present in a generic MLP, leading to it being derived from a Wiener filter that has zero-mean simple Gaussian priors for speech and noise in a highly intricate nonlinear function. It is consequently challenging to calculate how an MLP should modify a Gaussian variable. Nevertheless, the subject of transforming a variable that is random through an MLP has already been covered in the literature. Sensitivity analysis of MLPs against noise is its main area of use.

Unfortunately, the relevant expectations have no known solutions. The Taylor series approximates the sigmoid in many papers on MLP performance. These estimates, however, are local, making them only applicable for low uncertainty levels and producing huge mistakes in all other cases.

By combining the acoustic transformation with the Taylor series of expansion, this approach avoids the locality issue. However, this method is not scalable to the sizes utilized in ASR systems and is not suitable for multilayer perceptrons. Some simplifications must be made in order to arrive at an overall model for the propagation through an MLP. MLPs used in ASR are often relatively large since they encompass the whole acoustic space given a stream of features. There are typically between 300 and 1000 nodes. Additionally, there is proof that an MLP's node outputs have a minimal statistical dependence. Assuming that each node's output follows the weighted and can be treated as an isolated Gaussian variable as a result of the central limit theorem is one way to simplify the situation given these characteristics. With this presumption, the issue is limited to the sigmoid function's sigmoid function propagation of a Gaussian variable. Additionally, just the first two minutes need to be transmitted when spreading the output of one layer to the next, significantly streamlining the procedure.

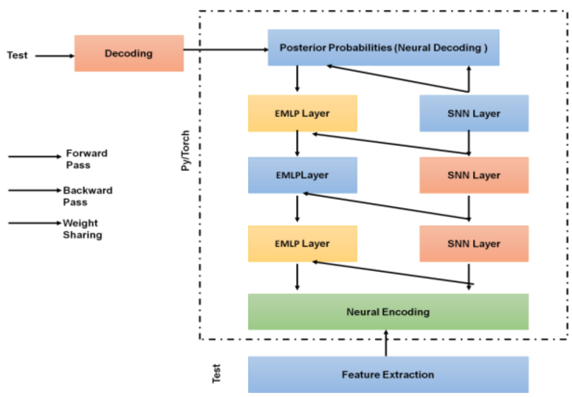

Figure 2: flowchart of EMLP-SNN

A type of neural network known as an enhanced multilayer perceptron integrated spiking neural network (EMLP-SNN) combines the spiking activity of biological neural networks with the benefits of conventional artificial neural networks, such as backpropagation (refer Figure 2).

1. Initialization: Set the network's weights and biases to modest random values.

2. Input Encoding: Make the input data into a spike-based form that the network can understand. Different encoding techniques, such as rate coding or temporal coding, can be used to accomplish this.

3. Feedforward: Using the input spikes, the current weights, and the current biases, calculate the stimulation of each neuron in the network.

4. Spike Generation: Use a spiking function to transform the neurons' activation values into spike trains.

5. Propagate spikes throughout the network, updating each neuron's activity in accordance with incoming points and the most recent weights and biases.

6. Learning: Based on the discrepancy between the expected and actual output, use a learning technique, such as backpropagation, to modify the network's weights and biases.

7. Repeat: Go back and forth between steps 3-6 until convergence or a predetermined number of epochs have passed.

The selection of the learning method, the spiking operation, and the encoding scheme are some essential factors to take into account when training an EMLP-SNN. Furthermore, the network's spiking activity might add complexity and call for specialized training methods like the highest point-timing-dependent plasticity.

4 Results and discussion

The participants in this study are undergraduates from our educational establishment. There are a total of 67 of them, 62 of whom are male and 25 of whom are female. Cool Edit, a piece of recording software, was used to record the subjects at a sampling rate of 18 kHz and a coding depth of 18 bits. The audio consists of ten sentences, each of which is a sentence that is widely used when speaking English. The computer system in question is equipped with an M1 Pro chip, featuring a 14-core GPU with a power consumption of 15 watts and an 8-core CPU capable of fluctuating between 0 and 22 watts. The system supports NVIDIA CUDA version 418.163, a parallel computing platform. Notably, the GPU operates under Rosetta 2, indicating that it is running software translated from a different architecture. The entire setup is powered by the macOS operating system (Table 2).

Table 2: Experimental setup

Equipment	Model
CUDA	NVIDIA CUDA 418.163
GPU	M1 Pro 14-Core GPU **15 W Rosetta 2**
CPU	M1 Pro 8-Core 0 W / 22 W
OS	Mac OS

In order to validate our claims regarding the superiority of the algorithm described in this research, we conducted side-by-side comparisons of the ANN, CNN, and PNN approaches in the same experimental environment. Table 3 presents the findings of a comparison of the two organizations' rates of recognition. As can be shown in Table 3 and Figure 3, the proposed method EMLP-SNN has a recognition rate of 97.52 percent, which is greater than the recognition rates of the models discussed earlier. As a direct consequence of this, the method that is described in this work is both logical and precise. It can be used to evaluate the effectiveness of multimedia training in college English classes.

Table 3: Accuracy comparison of existing methods with our proposed method

Model	Accuracy
ANN	91
CNN	90.56
PNN	93.22
EMLP-SNN	97.52

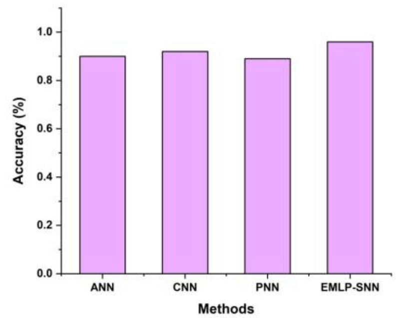

Figure 3: accuracy comparison

As can be seen in Figures 4 and 5, the suggested method of EMLP-SNN will result in a loss function value that is lower than 0.2. At the same time, ANN can never go lower than approximately 0.5. The "loss function values" of the CNN method drop to around 0.3 and then cease converging, while the PNN method drop to about 0.4. This demonstrates that our model is superior to others in terms of its ability to converge. This algorithm performs significantly better than the other approaches that were evaluated in terms of its effectiveness and speed of convergence in the experimentation, which are clearly explained in Tables (4 and 5)

Table 4: Comparison results of convergence performance

	ANN			PNN			CNN			EMLP-SNN
epoch	Loss function		epoch	Loss function		epoch	Loss function		epoch	Loss function
1.457543	1.337217		4.389439	1.309587		2.094912	1.077588		3.624597	1.077588
1.457543	1.337217		9.488389	1.128023		2.094912	1.077588		3.624597	0.90348
11.65544	1.286782		16.11702	0.984175		9.488389	0.822784		10.25323	0.729371
18.28408	1.193369		16.11702	0.984175		16.75439	0.59561		10.25323	0.729371
22.61818	1.085044		21.98082	0.810066		16.75439	0.59561		16.75439	0.545175
25.55008	0.968825		38.04251	0.656131		25.55008	0.444306		16.75439	0.545175
25.55008	0.968825		72.46042	0.560525		44.67114	0.376329		27.84461	0.328526
32.94356	0.860501		72.46042	0.560525		44.67114	0.376329		27.84461	0.328526
40.20956	0.762263		113.507	0.514915		73.22526	0.315808		32.94356	0.467111
40.20956	0.762263		173.5471	0.494741		73.22526	0.315808		41.73925	0.399134
59.33062	0.674112		224.1542	0.484654		106.241	0.293003		41.73925	0.399134
93.74853	0.618415		257.9347	0.507459		106.241	0.293003		50.53493	0.371067
134.0302	0.578067		288.6559	0.502635		152.3865	0.285547		50.53493	0.371067
134.0302	0.578067		288.6559	0.502635		200.699	0.300458		55.63388	0.194765
169.9778	0.563156		324.6035	0.494741		261.504	0.315808		71.69558	0.167136
204.3957	0.560525		335.5662	0.520177		261.504	0.315808		71.69558	0.167136

238.0488	0.557894		335.5662	0.520177		304.0802	0.323263		98.08264	0.134244
268.1326	0.555262		383.2414	0.520177		333.3992	0.335982		98.08264	0.134244
297.4516	0.563156		383.2414	0.520177		382.4766	0.33335		142.0611	0.106614
320.1419	0.557894		437.4177	0.520177		434.4859	0.343437		189.7363	0.101351
345.7641	0.545175		437.4177	0.520177		434.4859	0.343437		232.185	0.096527
380.9469	0.545175		495.2908	0.517546		496.8205	0.340806		232.185	0.096527
421.2286	0.545175		495.2908	0.517546		496.8205	0.340806		273.9964	0.08644

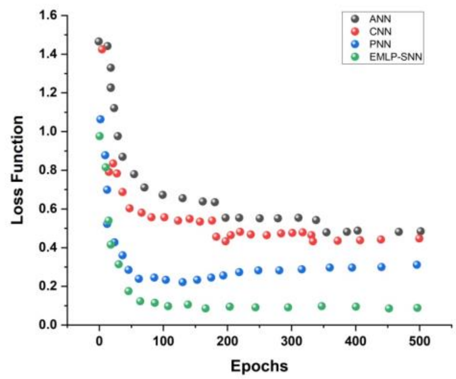

Figure 4: Comparison results of convergence performance.

Table 5: Comparison results of convergence speed

	ANN			PNN			CNN			EMLP-SNN
epochs	**Loss function**		**epochs**	**Loss function**		**epochs**	**Loss function**		**epochs**	**Loss function**
-0.97633	1.465114		4.215425	1.424389		1.936116	1.062891		0.543205	0.976413
12.95278	1.441986		15.10546	0.79139		9.280557	0.877868		0.543205	0.976413
18.01791	1.329364		21.69013	0.834629		12.19301	0.698879		10.04033	0.814518
18.01791	1.227803		27.51503	0.782843		12.19301	0.522404		14.34569	0.540001
18.01791	1.225289		36.25238	0.687315		23.84281	0.426876		18.01791	0.415312
23.08304	1.121213		36.25238	0.687315		23.84281	0.426876		30.42748	0.314253
28.90794	0.976413		47.14242	0.603351		36.25238	0.360509		45.62288	0.175486
28.90794	0.976413		47.14242	0.603351		45.62288	0.285092		45.62288	0.175486
36.25238	0.869321		66.13666	0.580223		61.70467	0.238836		63.85735	0.123197
54.36023	0.779827		66.13666	0.580223		85.76404	0.24487		63.85735	0.123197
70.44202	0.710443		81.33205	0.557096		103.9985	0.233306		86.52381	0.11465
70.44202	0.710443		101.7192	0.557096		130.2106	0.221742		86.52381	0.11465
98.80676	0.672735		101.7192	0.557096		152.7504	0.233306		107.5441	0.097556
130.2106	0.65564		122.8661	0.540001		174.6571	0.24487		107.5441	0.097556
161.4878	0.638043		122.8661	0.540001		193.5247	0.256434		138.1882	0.106103
180.482	0.635026		141.1006	0.548548		193.5247	0.256434		165.9198	0.085992
197.1969	0.554079		157.1824	0.533968		218.3439	0.273528		203.7816	0.094539
197.1969	0.554079		157.1824	0.533968		248.2281	0.282578		203.7816	0.094539

218.3439	0.554079		176.05	0.540001		248.2281	0.282578		243.7962	0.091522
250.3808	0.551565		182.6347	0.456037		280.8982	0.282578		243.7962	0.091522
278.7456	0.551565		197.1969	0.432909		315.9743	0.288109		294.8274	0.091522
310.7825	0.554079		197.1969	0.432909		359.661	0.296656		347.2515	0.097556
338.5141	0.542515		205.1745	0.464584		359.661	0.296656		400.4353	0.094539
354.4693	0.479165		219.7368	0.481679		394.6104	0.296656		452.0997	0.085992
386.6329	0.481679		236.5783	0.467601		440.4499	0.299673		496.5462	0.088506
403.3478	0.487712		261.2709	0.464584		495.7865	0.311237		496.5462	0.088506

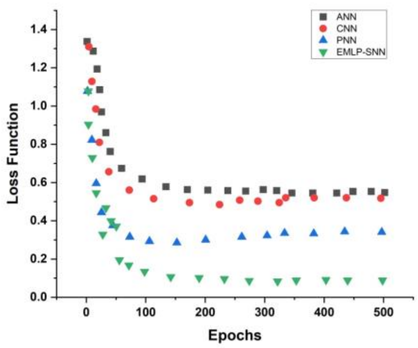

Figure 5: Comparison results of convergence speed

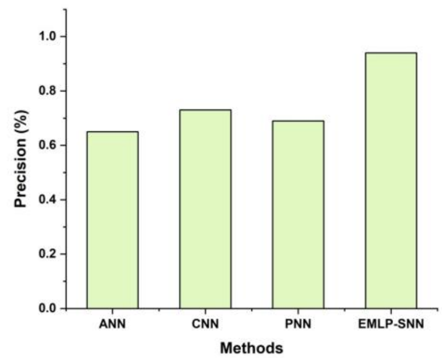

Figure 6: Precision

The factor that determines the test's level of precision is the ratio of the number of positive samples that can be anticipated to the number of positive examples that can be confidently predicted. Table 6 and Figure 6 illustrates a comparison between the proposed methodology and the present method's precision. The existing techniques ANN, CNN, and PNN each have 90%, 86.4%, and 93.8%, respectively, while the new EMLP-SNN strategy has 98.1%.It demonstrates that the proposed method is superior to others in terms of precision.

Table 6: Precision

Methods	Precision (%)
ANN	0.65
CNN	0.73
PNN	0.69
EMLP-SNN	0.94

4.1 Discussion

Our proposed method, the Enhanced Multilayer Perceptron integrated with a Spiking Neural Network (EMLP-SNN), represents a novel approach to addressing the limitations of existing methods such as ANNs, CNNs, and PNNs in the context of online teaching interactive systems for multimedia-assisted teaching. Compared to ANNs, EMLP-SNN reduces the demand for large labeled datasets by utilizing the benefits of spiking neural networks, which can process temporal input effectively and perform better with smaller datasets. When compared to computationally expensive CNNs, EMLP-SNN provides a more resource-efficient alternative, allowing for real-time interactions in online education without sacrificing performance. The application of spiking neural networks improves interpretability by offering a more transparent decision-making process, which is critical for instructional feedback scenarios and overcomes the black-box aspect of PNNs. Furthermore, EMLP-SNN shows enhanced adaptation to changes in teaching approaches and content, overcoming the limits of standard neural networks. This novel technique also includes measures to reduce overfittings, improve generalization capabilities, and ensure fair and unbiased evaluations. EMLP-SNN also focuses on data security and privacy while adhering to ethical considerations in educational technology applications.

5 Conclusion

Each of the everyday speech recognition techniques currently in use, EMLP-SNN, has hit bottlenecks that have never been seen before, and it is no longer possible to make any improvements to either their accuracy or their pace. As a reaction to these concerns, the primary focus of this study is on analyzing the results of implementing multimedia instruction into college English classes. In order to evaluate how words are spoken when spoken in English, a multilayer residual convolution neural network has been developed. The suggested algorithm has been tested, and it assists students in differentiating their pronunciation from the standard pronunciation, identifying and addressing mistakes in pronunciation, and improving the quality of oral English learning. There are several restrictions placed on online teaching interactive systems that make use of EMLP-SNN. The requirement for technical skills and infrastructure, high implementation costs, the possible challenge of engaging students, restricted feedback, the challenge of adapting to individual learners' needs, and the chance of technological faults are some of these challenges. It is vital to keep these restrictions in mind while utilizing these systems and to do so in a manner that makes the most of their benefits while minimizing the impact of any negatives they may have. Despite the fact that these systems have the potential to revolutionize teaching and learning, this is not the case. Integrating spiking neural networks with traditional multilayer perceptrons may introduce additional parameters and intricacies in the training process, requiring careful optimization and more computational resources.

In the future, we can expect online teaching interactive systems using enhanced multilayer perceptron integrated spiking neural network to become more accessible, adaptable, and engaging for students. With the use of data analytics, artificial intelligence, and virtual and augmented reality technologies, these systems will provide more personalized and immersive learning experiences. As a result, we can anticipate their increased adoption and integration into traditional educational methods, leading to a more effective and efficient learning experience for students.

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