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## Socialized Teaching of English Learning in Mobile Internet Technology



**Abstract:** - Distractions and multitasking can hinder the effectiveness of language learning, requiring innovative strategies to engage and maintain learners focus. Equitable access to mobile internet technology and ensuring accurate and culturally appropriate language learning materials are challenges in the socialized teaching of English learning in mobile internet technology. To overcome this issue, present for Socialized Teaching of English Learning in Mobile Internet Technology (STEL-MIT) is proposed. Initially, the data is collected from English education database. In pre-processing segment; it removes the noise and enhances the input data's utilizing Sub Aperture Keystone Transform Matched Filtering (SAKTMF). Afterward, the data's are fed to pre-processing. In pre-processing segment; it eliminates the missing data and enhances the input data's utilizing Sub Aperture Keystone Transform Matched Filtering (SAKTMF). The outcome from the pre-processing data is transferred to the ITFCZNN. The listening, speaking, reading, writing are successfully classified by using ITFCZNN. The MCOA is used to optimize the weight parameter of ITFCZNN. The proposed method is implemented using MATLAB, and several performance metrics, including accuracy, precision, recall, sensitivity, F1 score, and calculation time, are used to determine the proposed STEL-MIT method's efficiency. Proposed STEL-MIT method attains higher accuracy 16.65%, 18.85% and 16.45%; higher sensitivity 16.34%, 12.23%, and 19.12%; higher precision 14.89%, 16.89% and 20.67%, higher recall 16.34%, 12.23%, and 18.54% analysed to the existing methods, such as Access to Online Learning: Machine Learning Analysis from a Social Justice Perspective (AOL-ML-SJP), Design of Online Intelligent English Teaching Platform Based on Artificial Intelligence Techniques (OJET-AI), and Novel Attack Finding System for Investigating Pedagogical Challenges of Mobile Technology to English Teaching (IPC-MT-ET), respectively.

**Keywords:** English Learning Flexibility, English Teaching, High Order Synchro Extracting Transform, Interference-Tolerant Fast Convergence Zeroing Neural Network, Mobile Internet Technology.

### I. INTRODUCTION

"Socialized Teaching of English Learning in Mobile Internet Technology" focuses on utilizing mobile internet technology to create a collaborative and interactive learning environment for English language learners [1, 2]. This innovative approach aims to leverage the power of social learning to enhance language acquisition and proficiency, while also promoting communication and cultural exchange among students [3]. Through the use of mobile technology into English language instruction, teachers may provide more individualized and chances for learning that are interesting and satisfy the many needs and tastes of students in the contemporary digital age [4]. The socialized teaching of English learning in mobile internet technology faces a multitude of challenges as it endeavours to harness the power of mobile technology and social learning for English language education [5]. Ensuring equitable access to technology, addressing technical barriers, and curating high-quality content are pivotal in overcoming the digital divide and ensuring the efficacy of the learning platform. Additionally, concerns surrounding privacy, security, and digital distractions necessitate the implementation of robust measures to safeguard learners' online experiences [6, 7].

Furthermore, accommodating diverse proficiency levels, fostering cultural sensitivity, and adapting pedagogical practices underscore the complexities of integrating socialized teaching principles into English language instruction [8]. Despite these challenges, concerted efforts to mitigate obstacles and provide adequate support for learners and educators hold the promise of creating a more inclusive, engaging, and an effective learning atmosphere that equips pupils to succeed in the linked world of today [9, 10]. Quality assurance mechanisms should be established to curate relevant and engaging content, while robust data protection measures must be in place to safeguard learners' privacy and security [11]. Strategies to mitigate digital distractions and accommodate diverse proficiency levels should be developed, fostering an inclusive and supportive learning environment [12].

To overcome the challenges associated with the socialized teaching of English learning in mobile internet technology, the proposed approach is used. It is imperative that efforts to close the digital gap receive top priority in order to guarantee that all students have fair access to technology and the internet [13, 14]. Simultaneously, comprehensive training programs should be implemented to enhance both learners' and educators' digital literacy skills, enabling them to navigate the technological landscape effectively. Additionally, cultural competence training for educators can promote sensitivity and appreciation for diverse perspectives [15].

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By addressing these challenges collaboratively, the socialized teaching of English learning in mobile internet technology can unlock its full potential, offering learners transformative educational experiences in the digital age [16]. In order to foster technological innovation in pedagogy and enhance instruction, improvements in mobile technology pedagogy must be based on empirical data [17]. In order to cast light on these issues and offer recommendations for innovative teaching practices in digital education, this study looks into the difficulties instructors have while using mobile teaching practices [18].

The following is a summary of the principal contributions:

- Initially, the English education base dataset is used to collect the data.
- Using an Sub aperture Keystone Transform Matched Filtering to eliminate the missing data at English education database dataset in the pre-processing segment
- The pre-processed data's are fed into the DAGCN, in order to effectively categorize the listening, speaking, reading, and writing.
- Performance metrics such as accuracy, precision, sensitivity, specificity, error rate, and calculation time are assessed after the proposed ITFCZNN-MCOA approach is implemented.

The remaining sections of this study are organized as: sector 2 covers the relevant literature, sector 3 outlines the proposed approach, sector 4 gives results and a discussion, and sector 5 concludes.

## II. LITERATURE REVIEW

Many studies were suggested in the works related to deep learning based, socialized teaching of English learning, this review covers a few current works,

Jie and Sunze [19] have suggested the investigating pedagogical challenges of mobile technology to English teaching. The challenges that language teachers have while teaching students remotely in higher education. The semi-structured interviews included of twenty-eight university instructors discussing how mobile technology have an effect on higher education's teaching and learning. Given the prevalence of mobile technology in today's world of education, four key topics were discussed: disruptive pedagogy, technological mediation, English instruction, and learning flexibility. It provides high system storage volume and it attains low precision.

Sun et al. [20] have suggested A cutting-edge tool platform that enables students to enhance their English language proficiency depending on their personality and level of knowledge absorption was developed by an online intelligent English teaching system that leverages deep learning to assist it. An English teaching assessment implementation model based on decision tree technologies has been developed by using neural networks and the decision tree algorithm. It helps teachers improve their students' English proficiency by distilling rules and information into easily understood chunks from vast volumes of data. This system was designed using the same mental model as the artificial intelligence expert system. It provides high number of public text and it provides low precision.

McIntyre [21] have suggested a social justice viewpoint on machine learning analysis and online learning access. The first step to benefiting from education is having access to it. Large populations are unable to accrue such experience due to between-country disparities, despite the fact that cumulative online learning experience is associated to academic learning advances. In low- and middle-income nations, parents are less accessible and have fewer resources than in high-income nations. These infrastructural issues include uncontextualized learning materials and internet access. The current study gathered data on online learning in order to determine the characteristics that are necessary to gain admission to online education. To arrive at a final model, a data-led method was used after a machine learning model guided by theory was looked at. For feature significance, Shapley values were obtained using the final model.

She and Zhang [22] have developed convolutional neural network in a distributed setting, and suggests a time-based scheduling approach and parallel computing data for optimizing distributed convolutional neural networks. The usefulness of video English curricula was also examined in this article. Research indicates that as network technology advances, information technology was being utilized by educational institutions more and more, allowing students to engage in remote, self-directed learning. The network teaching platform of today was multifunctional, offering features like online tests and knowledge point learning, among others. In order to answer the concerns raised in the video English course, the platform system was designed and developed with attention for the project response theory. It attains high precision and it provides low accuracy

Zhang and Wang [23] have developed a clever knowledge discovery system that uses a BP neural network with a genetic algorithm to teach quality evaluation. The features consist of three parts of the factors: the

teaching conditions, the teaching method. The evolutionary algorithm was then introduced to re-optimize the learned parameters. A performance assessment of the suggested evaluation methodology was also conducted using a real-world course-teaching dataset. It provides low specificity and it attains low accuracy.

He et al. [24] have presented suggested the shared IoT system focused on teaching English translation with a DL-based TC. The goal was to further the reform of English translation instruction while adjusting to the present state of social improvement. Based on the Internet of Things (IoT), text categorization (TC), and deep learning (DL) theories, examines the state of English translation education today. Furthermore, a selection of 100 text categories was made as study items from North-western Polytechnic University's English text corpus. The simulated annealing methodology was introduced to examine the data after they were classified using the DL-based TC method. It attains high accuracy and it attains low error rate.

Rehman et al. [25] have suggested enterprise architectures utilizing machine learning and internet of things applications. The IoT has become widely used across a number of industries due to its quick expansion, which has allowed for improved efficiency and effective services. It was now standard practice to integrate Internet of Things technology with already-existing enterprise application systems. To incorporate IoT and cloud technologies, this integration does, however, require re-evaluating and revising existing Expert Systems (ES) and Enterprise Architecture (EA) models. Businesses need to take a diversified approach and automate a number of processes, such as data management, operations, and technological infrastructure. Within EA, machine learning (ML) was a potent IoT and intelligent automation technology. Even with its potential, ML applications for IoT systems and services still require a lot of focused effort. It provides low accuracy and it provides low precision.

### III. PROPOSED METHODOLOGY

This section presents the proposed STL-MIT, or Supervised ITFCZNN. Block diagram of proposed STEL-MIT is illustrated in Figure 1. Pre-processing, prediction, optimization, and data acquisition are the five processes in this procedure. As a result, a thorough explanation of each step is provided below.

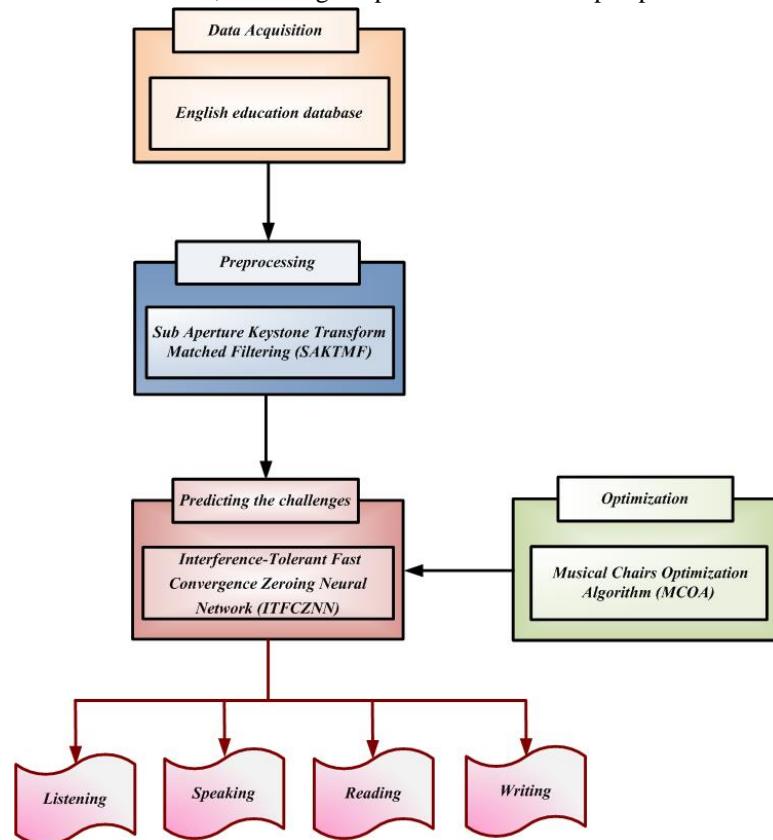


Figure 1: Block diagram for the proposed STEL-MIT method

#### A. Data Acquisition

A database on English schooling was used in this investigation [26]. Students who are teaching second languages might use the database as a research tool.

*B. Pre-processing using Sub Aperture Keystone Transform Matched Filtering*

In this section, Sub Aperture Keystone Transform Matched Filtering (SAKTMF) is used eliminate the missing data [27]. Missing data and duplicate packets could be present in the input data. These data are collected by an English education database. If the data is sensitive, make sure it's properly secured and that only people with permission may access it. Based on the phase connection derivation among sub apertures, a unique SAKTMF method is created. Thus the aperture is given by the equation (1)

$$QR(k_t, k_n) = \sum_{l=1}^L QR_l(k_t, k_n, l) \tag{1}$$

Where,  $QR$  represents the whole data,  $(k_t, k_n)$  denotes the demodulation operation,  $L$  indicates the sub blocks and  $l$  represents the words. Pedagogies were called upon to organize and carry out interactive activities in both formal and informal contexts, allowing students to engage in self-directed learning via an online digital platform. Then the Doppler direction of the information data is given by the equation (2)

$$qR_l(k_t, h_n) = SA_{k_n}[qR_l(k_t, k_n, l)] \tag{2}$$

Here,  $SA_{k_n}$  represents the operation being carried out in related to  $k_n$ ,  $h_n$  denotes the Doppler frequency. English instruction was aided by mobile pedagogy, which provided rich, timely, practical, and contextual materials in adaptable environments. Making invariant predictions by spanning many perspectives of the same scene is the primary objective of SAKTMF. Then, it is given in equation (3)

$$W\{\alpha\} = \sum_{l=1}^L \left| qR_l \left( \frac{2}{a} t(\alpha, lD_a), h(\alpha, lD_a) \right) \right| \tag{3}$$

Here,  $\alpha$  represents the searching parametric space vector,  $t(\alpha, lD_a)$ , and  $h(\alpha, lD_a)$  represents the Doppler position and range corresponding to the sub aperture index  $l$ . Then, every frame is resized by the equation (4)

$$\left( \frac{h_a}{h_t + h_a} \right)^k \approx 1 - k \frac{h_t}{h_a} \tag{4}$$

Where,  $h_t$  represents the range frequency variable,  $h_a$  denotes the preliminary integration,  $k$  indicates the linear range. The pre-processing technique that methodically identifies, arranges, and provides insight into meaningful patterns within a data collection. SAKTMF is deleting the unnecessary words, pauses, speech enhancers, and vocal cues by figuring out the equation (5)

$$\hat{y}_1 = -\frac{2}{\lambda} [\arg \max \{SAKTMF(k_t, h_n; \hat{y})\}] \tag{5}$$

Here,  $\hat{y}$  represents the corresponding searching motion parameters vector,  $k_t$  denotes the demodulation operation,  $\lambda$  and represents the data. Finally, the data is pre-processed by SAKTMF, which is eliminated missed data. These pre-processed data are fed into the prediction using ITFCZNN.

*C. Prediction using Interference-Tolerant Fast Convergence Zeroing Neural Network (ITFCZNN)*

In this section, ITFCZNN is discussed [28]. ITFCZNN is used to classify the listening, speaking, reading, and writing. Furthermore, compared to exponential, fixed-time convergence generate with conditional information. Then it is adjusted to the output type of ITFCZNN is given below,

$$\varphi(a) = \left( |a|^{1/s} + |a|^{1/s} \right) \text{sgn}(a) + G_1 a + G_2 \text{sgn}(a) \tag{6}$$

Where,  $\varphi(a)$  is the element of  $\Phi$ ;  $\Phi$  denotes the activation function;  $\text{sgn}$  represents the is the signal function;  $G_1 a$  denotes the noise suppression in the convergence;  $\left( |a|^{1/s} + |a|^{1/s} \right)$  represents the fixed-time convergence than the advanced exponential or finite time convergence, and then the value of  $l > 0$ ,  $G_1 > 0$  and  $G_2 > 0$  is considered. The dynamic force between instructors, students, and the tasks is emphasized by mobile pedagogy, which implies that learning happens as a result of interactions within the learning community; thus; it is given in below equation

$$X(T_m)A(T_m) = -X(T_m)A(T_m) - \lambda \Phi(X(T_m)A(T_m) - P) + Q(T_m) \tag{7}$$

(7)

Where,  $\Phi$  represents the activation function;  $X(T_m)A(T_m)$  realize the simultaneous fixed-time convergence and suppression and  $Q(T_m)$  is the additive frames, which may be either time-varying or constant,  $\lambda$  represents the label information. Teaching papers are encrypted by the card in file categorization using an encryption technique. A fatal flaw in the single key-based encryption is that it is easily cracked. Then it is given in equation (8)

$$T_{t\max} \leq \frac{1}{G} \left| \frac{1}{1-l/h} + \frac{1}{h/l-1} \right| = \frac{1}{G} \left| \frac{1+h/l}{1-h/l} \right| \tag{8}$$

Whereas  $\frac{1}{G}$  is used as opposites to be compared with this work,  $T_{t\max}$  solely refers to the system's design parameters,  $l$  and  $h$ , and is unrelated to the starting state,  $a(0)$ . This method states that the ITFCZNN model's dynamic error matrix  $f(T_m)$  may be written as  $\frac{em(T_m)}{en} = \lambda\Phi(f(T_m))$  and its  $m^2$  subsystem can be obtained (9)

$$\frac{em(T_m)}{en} = -\lambda\varphi(f_{ij}(T_m))\text{sgn}(f_{ij}(T_m)) \tag{9}$$

Where  $\frac{em(T_m)}{en}$  is the  $ij^{th}$  subsystem's bounded time  $f_{ij}$ ;  $f_{ij}(T_m)$  is the method used to demonstrate the ITFCZNN model's fixed-time convergence;  $\lambda$  represents the label information,  $\text{sgn}$  denotes the signum function,  $\varphi$  communication system. The ITFCZNN is analysed the coding in accordance with patterns derived from the study's major ideas, which included technology, pedagogy, English instruction, and learners. It is formulated in equation (10), (11)

$$\frac{em(T_m)}{en} = 2f_{ij}(T_m)f_{ij}(T_m) \tag{10}$$

$$\frac{em(T_m)}{en} = 2f_{ij}(T_m)(-\lambda\varphi(f_{ij}(T_m))+m_{ij}(T_m)) \tag{11}$$

Let  $\frac{em(T_m)}{en}$  be the bounded time  $f_{ij}$  of the  $ij^{th}$  subsystem;  $f_{ij}(T_m)$  is used to demonstrate the fixed-time convergence of the ITFCZNN model;  $\Phi$  is denoted as the activation function;  $\varphi(a)$  is the element of  $\Phi$ ; and  $\lambda$  is the ITFCZNN model's fixed-time convergence. Some categories are relatively few and unrepresentative. Finally, ITFCZNN classified listening, reading, writing, and speaking. Thanks to its ease of use and pertinence, the ITFCZNN classifier takes into account the artificial intelligence-based optimization method. Using the MCOA, the ITFCZNN is optimized in this work. In this case, MCOA is used to adjust the ITFCZNN's weight and bias  $\varphi, G_1$  parameter.

**D. Stepwise Procedure for Musical Chairs Optimization Algorithm**

Here, a detailed process for utilizing Musical Chairs Optimization Algorithm (MCOA) to get ideal ITFCZNN values is explained [29]. A unique optimization technique known as the MCOA has been mathematically implemented. Every participant in the MCA represents a distinct solution, and the chair adjacent to each player represents the best previous solution. In MCA three primary elements comprise the logic employed in the MCA implementation: the initialization of the optimization, the tracking section for the ideal solution, and the evaluation technique. The comprehensive step's technique designated below,

**Step 1: Initialization**

The objective function will use the starting position of the participants, which will be chosen at random during the start up phase, to calculate each participant's unique fitness rating. Then it is given in equation (12)

$$[aV_c, aQ_c] = \min(\vec{V}_c) \tag{12}$$

Where,  $aV_c$  represents the data's optimal fitness value,  $aQ_c$  denotes the location of the data,  $\vec{V}_c$  denotes the vector representing the fitness value of data.

**Step 2: Random Generation**

The creation of the input parameters is done at random after startup. In this case, the explicit hyper parameter situation is taken into consideration while choosing the values of optimum fitness.

**Step 3: Fitness Function**

The starting values and outcome are determined at random. The results of weight parameter optimization  $\varphi, G_1$  are used to assess fitness values. As a result, equation (13) provides it.

$$fitness\ function = Optimizing[\varphi G_1] \tag{13}$$

**Step 4: Exploration Phase**

To improve exploration performance, most optimization phases require a high number of search agents at the start of the process. The fastest individual to find the global optima is employed. The Exploration phase is given in equation (14)

$$\sigma_n = \left( \frac{\Gamma(1 + \beta) \cdot \sin(\pi \cdot \beta / 2)}{\Gamma\left(\frac{1 + \beta}{2}\right) \cdot \beta \cdot 2^{\left(\frac{\beta - 1}{2}\right)}} \right) \tag{14}$$

Here,  $\sigma_n$  represents the variance of  $n$ ,  $\beta$  denotes the Levy flights that provide a random convergence time,  $\pi$  indicates the new position of the data. Then, the random variable of the data is given in equation (15)

$$Q_{q,t}^f = Q_{q,t}^{f-1} + U \cdot \frac{|n|}{v^{1/\beta}} \cdot R \tag{15}$$

Here,  $R$  represents the random variable,  $U$  denotes matrices with a uniform distribution,  $f$  indicates the first search agent count,  $Q$  and denotes the generation.

**Step 5: Exploitation Phase for Optimizing  $\varphi, G_1$**

The last phase, well-known as "exploitation," to improve exploitation, decreases the convergence time and uses fewer search agents in the later stages; Thus, the exploitation phase is given in equation (16)

$$F = f \rightarrow \max(\vec{V}_q^f) - \min(\vec{V}_q^f) \leq \varepsilon_1 \tag{16}$$

Here,  $F$  represents the entire count of iterations at which the halting strategy is verified,  $\vec{V}_q^f$  denotes the vector during iteration  $f$  that represents the values of global agents,  $\varepsilon_1$  indicates the tolerance value that was established. The starting number of data is given in equation (17)

$$W = 2 * (F - T_0 + 1) + \sum_{i=T_0}^2 i \tag{17}$$

Where,  $F$  represents the entire count of iterations,  $T_0$  signifies the starting count of data,  $W$  represents the objective function.

**Step 6: Termination**

The MCOA Algorithm is used in this step to optimize the weight parameter values  $\varphi, G_1$  from the ITFCZNN. This process repeatedly repeats step 3 until the stopping conditions  $aV_c = aV_c + 1$  are satisfied. Finally, TEL-MIT predicts the challenges with higher accuracy with less Error rate. Figure 2 shows Flowchart for MCOA optimizing ITFCZNN.

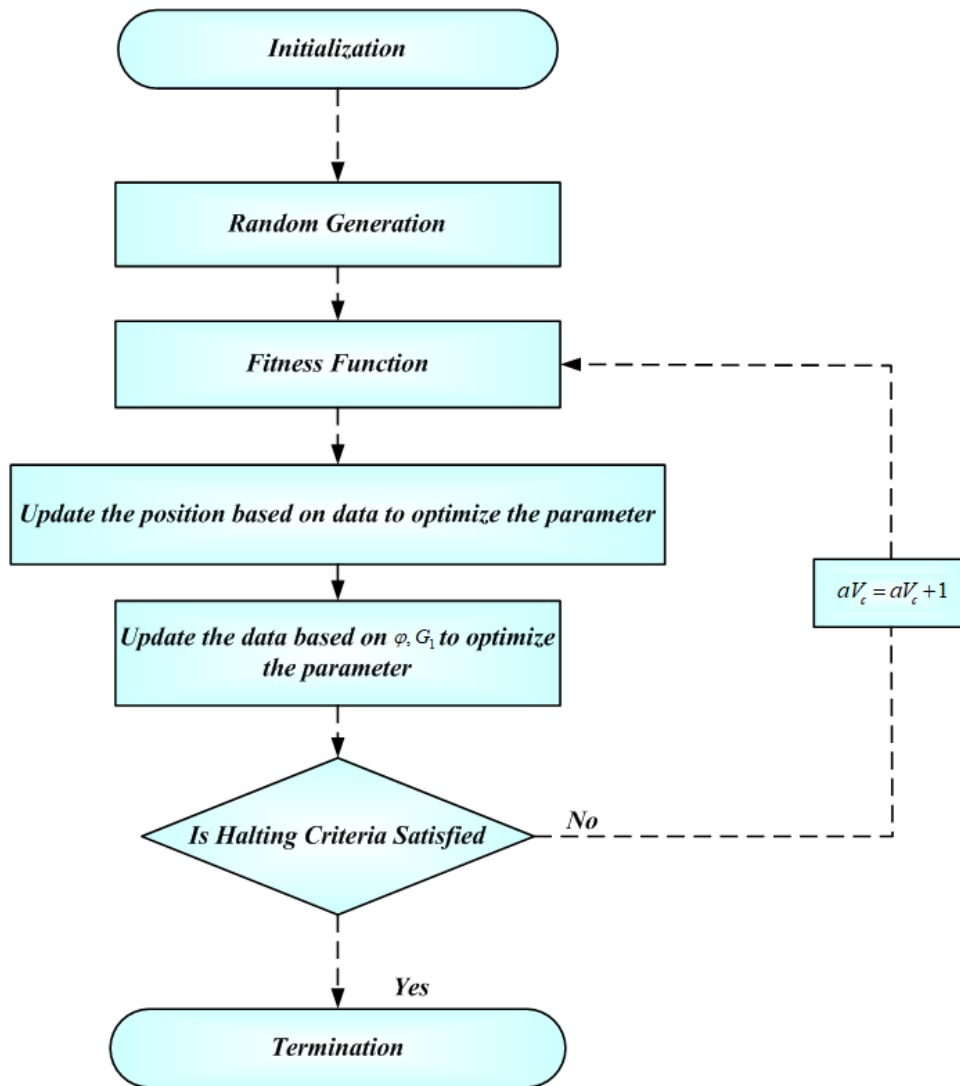


Figure 2: Flowchart for MCOA optimizing ITFCZNN

#### IV. RESULT AND DISCUSSION

This sector discusses the experimental outcomes of the proposed method. Next, MATLAB is used to simulate the proposed method using the specified performance criteria. The obtained outcome of the proposed STEL-MIT approach is analysed with existing systems like IPC-MT-ET, OIET-AI, and AOL-ML-SJP correspondingly.

##### A. Performance measures

This is a crucial phase in selecting the best classifier. Performance variables like error rate, computing time, sensitivity, specificity, accuracy, and precision are analyzed to assess performance.

##### 1) Accuracy

The capability to measure precise value is called as accuracy. A statistic called accuracy may be used to characterize the model's performance in all classes. The following equation is used to measure it (18)

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \tag{18}$$

In this step  $TP$  represents True positive  $TN$  represents True negative  $FP$  represents false positive  $FN$  represents false negative.

##### 2) Precision

Precision estimation include many positive labels had expected with high accuracy, it is given an equation (19)

$$Precision = \frac{TP}{(TP + FP)} \tag{19}$$

3) *F1-Score*

F-score is a metric used to analyze the performance of proposed ISIA-DAGCN-COA technique. It is calculated in Eqn (20),

$$F\ score = F1score = \frac{TP}{TP + \frac{1}{2}[FP + FN]} \tag{20}$$

B. *Performance Analysis*

Figure 3 to 8 portrays simulation results of STEL-MIT technique. Then, the proposed STEL-MIT technique is likened with existing IPC-MT-ET, OIET-AI, and AOL-ML-SJP method.

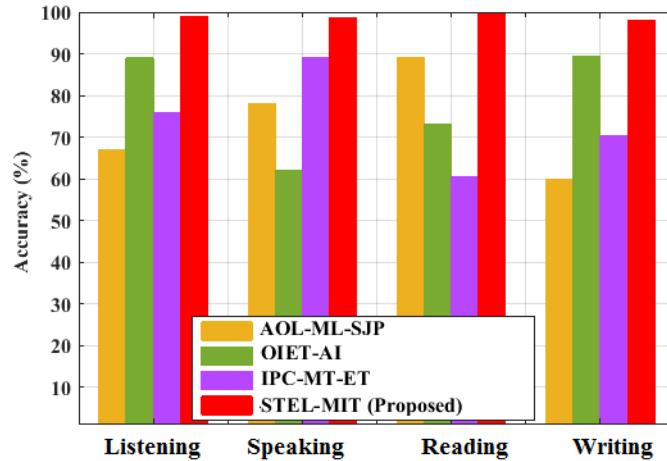


Figure 3: Performance analysis of Accuracy

Figure 3 depicts accuracy analysis. Accuracy for the listening category is 50.56%, 20.76%, and 35.97% higher when using the proposed STEL-MIT approach. 20.46%, 35.58%, and 23.54% more in the speaking category and 21.45%, 30.76%, 18.43% higher for the classification of reading, 21.44%, 30.86%, 15.43% higher for the classification of writing, when evaluated to existing IPC-MT-ET, OIET-AI, and AOL-ML-SJP method respectively.

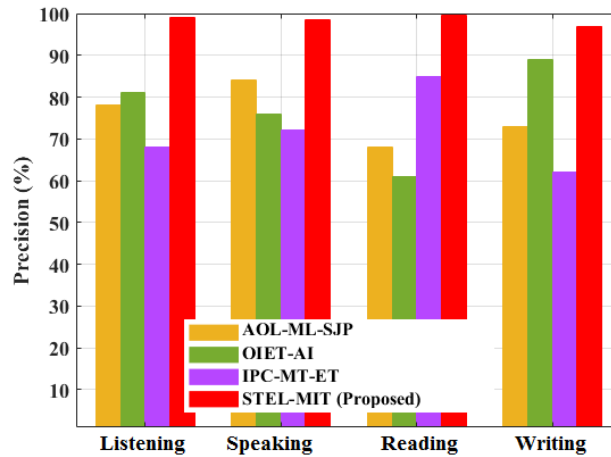


Figure 4: Performance analysis of Precision

The Performance analysis of Precision is presented in Figure 4. Here, a direct comparison with proposed approaches is offered to show how the suggested method's precision is higher. The proposed method provides for a more extensive analysis of a proposed and has higher precision than existing methods due to its wider consideration of factors. The performance of the proposed STEL-MIT technique results in precision that are 30.56%, 21.76%, 35.97% higher for the classification of listening, 21.46%, 33.58%, 23.54% higher for the classification of speaking and 21.45%, 30.76%, 18.43% higher for the classification of reading, 20.44%, 30.86%, 15.43% higher for the classification of writing when evaluated to existing IPC-MT-ET, OIET-AI, and AOL-ML-SJP method respectively.



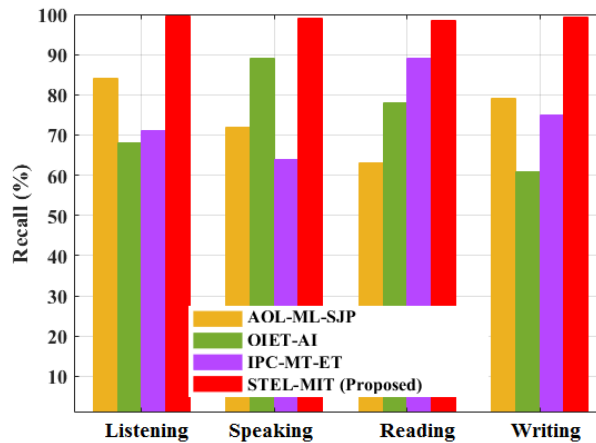


Figure 5: Recall value comparison between the proposed and existing techniques.

The Recall value comparison between the proposed and existing techniques is presented in Figure 5. Recall for the listening category is 23.56%, 22.76%, and 31.97% greater when the proposed STEL-MIT approach is used. 31.58%, 22.54%, and 22.46% greater for the speaking category and 22.45%, 29.76%, 17.43% higher for the classification of reading, 19.44%, 29.86%, 14.43% higher for the classification of writing when evaluated to existing IPC-MT-ET, OIET-AI, and AOL-ML-SJP method correspondingly.

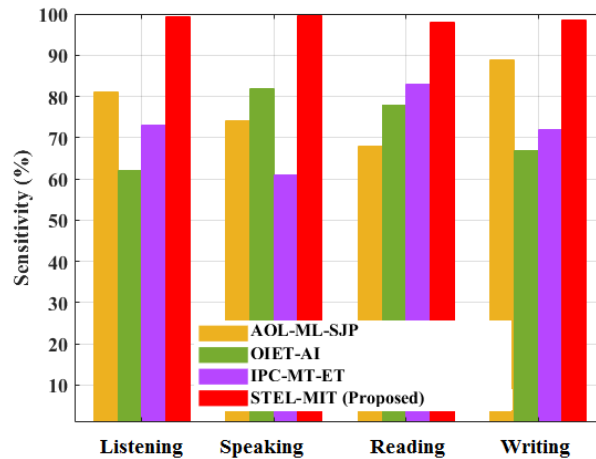


Figure 6: Performance analysis of sensitivity

Figure 6 demonstrates the analysis of specificity. The performance of the proposed STEL-MIT technique results in sensitivity that are 30.56%, 21.76%, 35.97%, In comparison to the existing IPC-MT-ET, OIET-AI, and AOL-ML-SJP models, the results are higher for the classification of listening, 21.46%, 33.58%, 23.54% higher for the classification of speaking, and 21.45%, 30.76%, 18.43% higher for the classification of reading, 20.46%, 35.58%, 23.54% higher for the classification of writing.

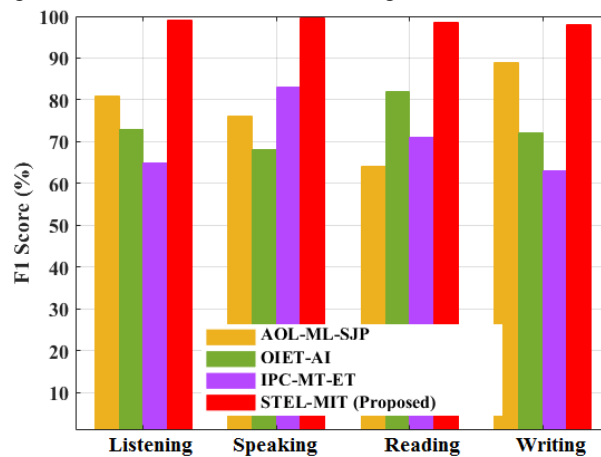


Figure 7: Comparing the proposed and existing approaches with the F1-score value.

The Comparing the proposed and existing approaches with the F1-score value is presented in Figure 7. Recall for the listening category is 23.56%, 22.76%, and 31.97% greater when the proposed STEL-MIT approach is used. 31.58%, 22.54%, and 22.46% greater for the speaking category and 22.45%, 29.76%, 17.43% higher for the classification of reading, 19.44%, 29.86%, 14.43% higher for the classification of writing when evaluated to existing IPC-MT-ET, OIET-AI, and AOL-ML-SJP method correspondingly.

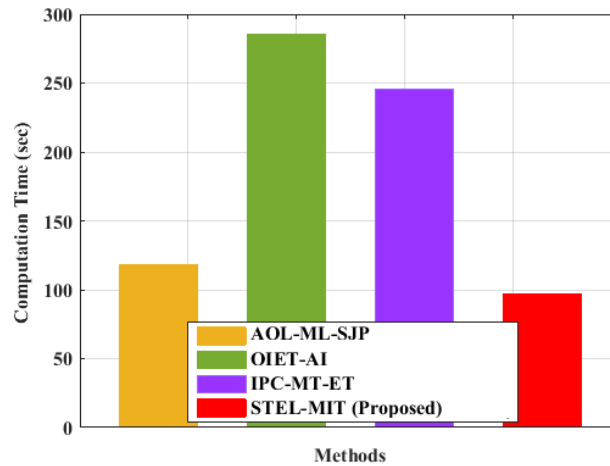


Figure 8: Performance analysis of Computational time

Figure 8 portrays the performance analysis of Computation Time. When compared to existing approaches, the proposed STEL-MIT method achieves 35.136%, 39.04%, and 38.81% reduced computing times such as IPC-MT-ET, OIET-AI, and AOL-ML-SJP respectively.

### C. Discussion

An STEL-MIT model for socialized teaching of English learning from Qualitative interview data set is developed in this paper. The STEL-MIT method involves encompasses SAKTMF based data pre-processing. Instance of Qualitative interview data set, the average highest outcomes of the approach were compared to the average results given in existing methods like IPC-MT-ET, OIET-AI, and AOL-ML-SJP respectively. The accuracy values of IPC-MT-ET, OIET-AI, and AOL-ML-SJP are 77.5%, 62.6% and 75.4% respectively, lesser than proposed method. Similar to this, whereas the average specificity value of comparison techniques is 83.44%, the specificity value of the suggested method is 98.93%.The proposed method STEL-MIT has high specificity and accuracy evaluation metrics than existing methods. Therefore, the comparative techniques are economically more expensive than the proposed method. It effectively addresses the challenges associated with the socialized teaching and demonstrates superior performance compared to existing methods.

## V. CONCLUSION

In present study, Interference-Tolerant Fast Convergence Zeroing Neural Network for Socialized Teaching of English Learning in Mobile Internet Technology (STEL-MIT) is successfully implemented. The pre-processing result is forwarded to the ITFCZNN is to efficiently predict the difficulties associated with disruptive pedagogy, technological mediation, teaching English, and flexible learning. The proposed STEL-MIT approach is implemented in MATLAB utilization of Qualitative interview data set. Various scenarios are examined for the proposed method, including recollection, calculation time, sensitivity, specificity, accuracy, and precision. Presentation of proposed STEL-MIT method covers 31.56%, 32.67% and 34.67% lower error rate; 32.14%, 23.43%, and 18.23% higher specificity; and 29.47%, 38.76% and 28.78% lower computational time analyzed to the existing approaches such as IPC-MT-ET,OIET-AI and AOL-ML-SJ respectively.

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