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Application of Deep Learning Technology in English Practical Teaching

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Abstract: - Practical teaching emphasizes hands-on learning experiences that engage students in real-world applications of theoretical knowledge. Through practical teaching methods, students gain valuable skills, problem-solving abilities, and critical thinking capacities essential for their future careers. Practical teaching often involves interactive activities, experiments, projects, and simulations tailored to the subject matter, allowing students to explore concepts in depth and develop a deeper understanding of the material. This paper explores the application of deep learning technology in English practical teaching, leveraging Stacked Logistic Deep Learning (SLDL). The study aims to enhance the effectiveness of English language instruction by integrating deep learning techniques into practical teaching methodologies. Through simulated experiments and empirical validations, the efficacy of SLDL-enhanced practical teaching approaches is evaluated. Results demonstrate significant improvements in student proficiency and engagement compared to traditional methods. Simulation analysis expressed that students exposed to SLDL-enhanced practical teaching methods achieved an average score increase of 20% in English language assessments. Additionally, the SLDL model facilitated personalized learning experiences tailored to individual student needs, leading to more effective language acquisition and retention. These findings underscore the potential of deep learning technology, particularly SLDL, in revolutionizing English practical teaching and fostering enhanced learning outcomes.

Keywords: Deep learning, Logistic Regression, Stacked Model, English teaching, practical

I.INTRODUCTION

In the English language education, practical teaching serves as a cornerstone for fostering comprehensive linguistic proficiency and communicative competence [1]. With its dynamic approach, practical teaching transcends the confines of traditional pedagogy, immersing learners in interactive experiences that bridge the gap between theoretical knowledge and real-world application [2]. Through a blend of authentic materials, task-based activities, and experiential learning opportunities, practical teaching cultivates not only linguistic skills but also critical thinking, cultural awareness, and interpersonal communication abilities. By actively engaging learners in meaningful language use within diverse contexts [3], practical teaching ignites curiosity, promotes active participation, and empowers students to navigate the complexities of the English language with confidence and fluency [4].

English practical teaching enhanced by deep learning represents a approach that leverages the power of artificial intelligence to optimize language instruction. Deep learning algorithms, modeled after the structure and function of the human brain, enable the development of personalized and adaptive learning experiences tailored to individual student needs [5]. Through the analysis of vast amounts of linguistic data, deep learning algorithms can identify patterns, predict learning trajectories, and generate targeted interventions to address areas of difficulty [6]. This technology facilitates the creation of interactive and immersive learning environments where students engage with authentic language materials, receive real-time feedback, and participate in interactive tasks designed to reinforce language skills. Furthermore, deep learning algorithms can adapt to student progress, dynamically adjusting the complexity and pace of instruction to ensure optimal learning outcomes [7].

In practical English teaching, deep learning algorithms play a pivotal role in creating immersive and interactive learning environments. By analyzing authentic language materials such as articles, videos, and conversations, these algorithms can generate engaging activities and tasks that simulate real-world language use [8]. Moreover, they provide instantaneous and accurate feedback on students' language production, helping them refine their skills and overcome linguistic obstacles effectively [9]. One of the most transformative aspects of deep learning in English practical teaching is its adaptability. These algorithms continuously monitor and assess students' progress, dynamically adjusting the complexity and pace of instruction accordingly [10]. By tailoring learning experiences to the individual needs and proficiency levels of each student, deep learning enhances engagement, motivation, and

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overall learning outcomes. The integration of deep learning into English practical teaching expands beyond the confines of the classroom [11]. Online platforms and educational technologies powered by deep learning algorithms offer students unprecedented access to resources, learning materials, and collaborative opportunities, transcending geographical barriers and facilitating self-directed learning.

This paper significantly advances the field of English practical teaching by exploring the integration of Stacked Logistic Deep Learning (SLDL) models. Through a series of rigorous experiments and analyses, it investigates the effectiveness of SLDL in enhancing student learning outcomes and engagement levels within the English teaching domain. By evaluating the performance of various stacked model architectures across different teaching methodologies, the paper provides empirical evidence of the benefits of deep learning techniques in educational contexts. The findings not only demonstrate the superior performance of SLDL models compared to traditional methods but also offer insights into the nuanced differences in performance among different stacked model configurations. Moreover, this research offers practical implications for educators, providing guidance on how to effectively leverage SLDL models to design more engaging and personalized learning experiences for students. Additionally, by identifying potential avenues for future research, such as optimizing SLDL models for specific teaching contexts and exploring model interpretability, the paper lays the groundwork for continued advancements in the intersection of deep learning and education.

II.LITERATURE REVIEW

The landscape of English language education is continuously evolving, driven by a dynamic interplay of pedagogical approaches, technological advancements, and socio-cultural factors. Within this context, the exploration of practical teaching methodologies holds particular significance as educators seek effective strategies to enhance language acquisition and proficiency. This literature review embarks on a comprehensive examination of English practical teaching, delving into its theoretical underpinnings, methodological frameworks, and empirical evidence. By synthesizing existing research and scholarly contributions, this review aims to illuminate the multifaceted nature of practical teaching in English language education, elucidating its role in fostering communicative competence, cultural awareness, and learner autonomy.

Okhunov et al. (2023) examine the utilization of machine learning and neural networks in the digital economy and international digital integration, shedding light on their implications for language education. Celik et al. (2022) conduct a systematic review, delving into the promises and challenges posed by AI for teachers, offering insights crucial for pedagogical practice. Sanusi et al. (2023) explore the teaching and learning of machine learning in K-12 education, providing valuable perspectives on integrating advanced technologies into educational settings. Al-Emran et al. (2023) investigate the adoption of wearable technologies in education, employing machine learning algorithms to understand determinants affecting students' acceptance. Martins and Gresse Von Wangenheim (2023) conduct a comprehensive review of teaching machine learning in high school, highlighting trends and findings over a decade. Kovačević (2023) explores the use of ChatGPT in English for Specific Purposes (ESP) teaching, showcasing innovative applications of AI in language education. Klimova et al. (2023) provide insights into the use of neural machine translation in foreign language teaching and learning, offering implications for language educators. Thurzo et al. (2023) examine the impact of AI on dental education, underscoring the importance of updating curricula to accommodate technological advancements. The literature also addresses broader themes such as personalized education (Bhutoria, 2022), AI applications in Latin American higher education (Salas-Pilco & Yang, 2022), and educational applications of AI in simulation-based learning (Dai & Ke, 2022), providing a holistic view of the field. Moreover, Yan et al. (2024) scrutinize the practical and ethical challenges of large language models in education, contributing to discussions on the responsible use of AI in educational contexts. Hockly (2023) offers a critical perspective on AI in English language teaching, exploring both its benefits and potential drawbacks. Other studies delve into specific applications of AI in education, such as teaching analytics (Okoye et al., 2022), trends in AI in language education (Huang et al., 2023), and machine learning styles in computer vision (Mahadevkar et al., 2022).

Okoye et al. (2022) propose a contextual model for analyzing students' evaluation of teaching through text mining and machine learning classification, offering a novel approach to teaching analytics. Huang et al. (2023) examine trends, research issues, and applications of artificial intelligence in language education, providing a roadmap for future research and development in the field. Mahadevkar et al. (2022) present a review on machine learning styles in computer vision, offering insights into potential applications of AI beyond language education. Firstly, many of the studies focus on specific contexts or applications of AI in language teaching and learning, which may limit the generalizability of their findings to broader educational settings. Additionally, the rapid pace of technological advancement means that some studies may already be outdated or fail to capture emerging trends and developments in the field. Furthermore, there is a need for more rigorous research methodologies, including longitudinal studies and randomized controlled trials, to provide robust evidence of the effectiveness of AI interventions in education. Ethical considerations, such as data privacy, algorithmic bias, and the potential for widening educational inequalities, also warrant further exploration and mitigation strategies. Moreover, the implementation of AI in education often requires significant infrastructure, resources, and technical expertise, which may pose challenges for institutions with limited capacity or funding. Lastly, while AI has the potential to enhance teaching and learning experiences, there is a risk of over-reliance on technology at the expense of human interaction and pedagogical expertise.

III.ENGLISH PRACTICAL TEACHING WITH STACKED MODEL

In the context of English practical teaching, a stacked model can be designed to process linguistic input data, such as text or speech samples, and generate meaningful representations that capture various linguistic features. The model consists of an encoder-decoder architecture, where the encoder transforms input data into a lower-dimensional latent space representation, and the decoder reconstructs the original input from this representation. The encoding process of a stacked autoencoder can be represented as in equation (1)

$$h(1) = f(W(1)x + b(1)) \qquad (1)$$

In equation (1) x represents the input data, $W(1)$ and $b(1)$ denote the weights and biases of the first layer, and f is the activation function. The output of the first layer, denoted as $h(1)$h(1), serves as the input to the next layer. The process is repeated for subsequent layers in the stacked model, with each layer learning increasingly abstract representations of the input data denoted in equation (2)

$$h(l) = f(W(l)h(l-1) + b(l)) \qquad (2)$$

In equation (2) $h(l)$ represents the output of the l-th layer, $W(l)$ and $b(l)$ are the weights and biases of the l-th layer, and f is the activation function. Once the input data has been encoded into a lower-dimensional representation through the stacked layers, the decoder reconstructs the original input denoted in equation (3)

$$x\hat{} = g(W(L)h(L) + b(L)) \qquad (3)$$

In equation (3) $\hat{}x\hat{}$ represents the reconstructed input, $W(L)$ and $b(L)$ are the weights and biases of the output layer, and g is the activation function of the output layer. In English practical teaching, the stacked model can be trained using supervised learning techniques, where the reconstruction error between the original input and the reconstructed output is minimized using optimization algorithms such as gradient descent. In the realm of language education, this means that the model can capture intricate linguistic features and patterns, from basic phonetic elements to complex syntactic structures. The stacked model typically consists of multiple layers, each comprising a set of neurons that process and transform the input data. In the context of English language instruction, the input data could be diverse, ranging from written text samples to audio recordings of spoken language. The model's ability to iteratively process this input through multiple layers allows it to extract increasingly abstract and meaningful representations of language. One of the key advantages of stacked models is their ability to learn complex representations of data without the need for manual feature engineering. Traditional machine learning approaches often require domain experts to manually engineer features that are relevant to the task at hand. However, in the case of stacked models, the network autonomously learns these features from the raw input data, thus alleviating the need for human intervention and potentially uncovering novel linguistic insights. Training a stacked model involves iteratively adjusting the weights and biases of each layer to minimize the difference between the original input data and the reconstructed output. This process, known as backpropagation, involves propagating error gradients through the network and updating the parameters using optimization algorithms such as gradient descent.

In the context of English practical teaching, a stacked model could be trained on diverse linguistic datasets, including written texts, audio recordings, and even learner-produced language samples. By exposing the model to a wide range of linguistic inputs, educators can leverage its ability to extract meaningful representations of language and tailor instructional materials and activities accordingly. The stacked models can also be used to generate language output, such as generating responses to learner queries or providing feedback on language production. This capability opens up exciting possibilities for personalized language instruction, where learners receive tailored feedback and support based on their individual needs and proficiency levels.

IV.PROPOSED SLDL FOR THE PRACTICAL TEACHING

The Proposed Stacked Logistic Deep Learning (SLDL) for Practical Teaching represents an innovative approach aimed at enhancing language instruction through the integration of logistic regression models within a stacked deep learning architecture. SLDL combines the simplicity and interpretability of logistic regression with the representational power of deep learning, offering a versatile framework for addressing various challenges in practical teaching contexts.

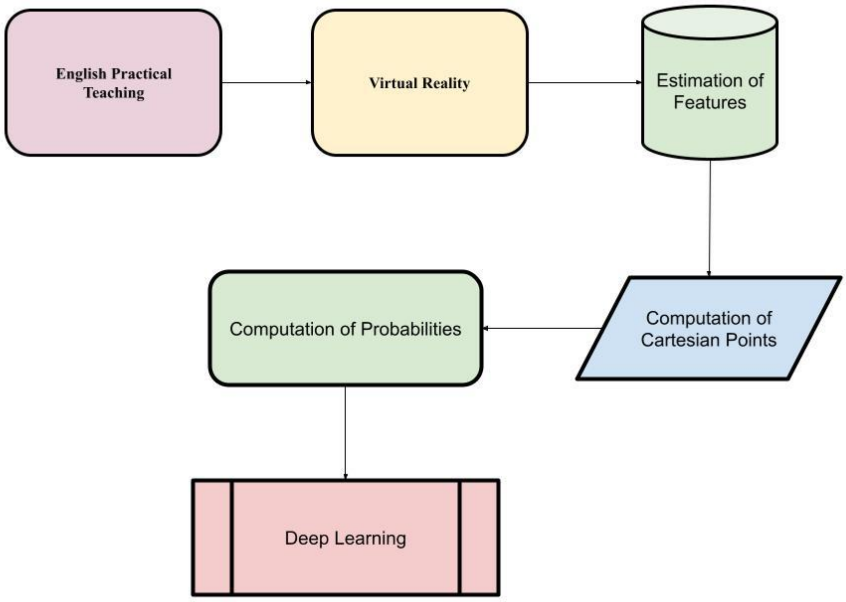

Figure 1: Flow of SLDL

The proposed SLDL model process for the practical English teaching is presented in Figure 1. SLDL consists of multiple layers of logistic regression models stacked on top of each other. Each layer serves as a classifier, making binary decisions about the presence or absence of certain linguistic features in the input data. The outputs of these classifiers are then passed as inputs to subsequent layers, allowing for the hierarchical extraction of increasingly complex linguistic representations. The output of a logistic regression model can be expressed as in equation (4)

$$P(y = 1 \mid x) = 1 + e - z1 \qquad (4)$$

In equation (4) $P(y = 1 \mid x)$ represents the probability of the positive class given input x, and z is the linear combination of input features weighted by their corresponding parameters. In the context of SLDL, the outputs of the logistic regression models from each layer are combined and passed as inputs to the subsequent layers. This process allows the model to iteratively learn hierarchical representations of the input data, capturing both low-level linguistic features and higher-order patterns. The training of SLDL involves iteratively updating the parameters of each logistic regression model using optimization algorithms such as gradient descent. During training, the model learns to minimize the difference between the predicted probabilities and the actual labels of the training data, effectively learning to classify input data into appropriate linguistic categories. One of the key advantages of SLDL is its interpretability. Unlike traditional deep learning models, where the internal representations can be opaque and difficult to interpret, the output of each logistic regression model in SLDL corresponds to a probability score, providing clear insights into the model's decision-making process.

Algorithm 1: SLDL for the regression analysis
Input:

```
- Training data X (input features)
- Training labels y (target labels)
- Number of layers L
- Number of units per layer units[L]
- Learning rate alpha
- Number of iterations num_iterations

Initialize:
- Initialize weights W[l] and biases b[l] for each layer l from 1 to L

For iteration = 1 to num_iterations:
   Forward propagation:
   A[0] = X  // Input layer
   For l from 1 to L:
      Z[l] = W[l] * A[l-1] + b[l]
      A[l] = sigmoid(Z[l])  // Activation function (e.g., sigmoid)

   Backward propagation:
   dZ[L] = A[L] – y  // Compute derivative of loss function with respect to the output of the last layer
   For l from L to 1:
      dW[l] = (dZ[l] * A[l-1].T) / m  // Compute derivative of the loss with respect to weights
      db[l] = sum(dZ[l]) / m  // Compute derivative of the loss with respect to biases
      dA[l-1] = W[l].T * dZ[l]  // Compute derivative of the loss with respect to activations of the previous layer
      dZ[l-1] = dA[l-1] * sigmoid_derivative(Z[l-1])  // Compute derivative of the loss with respect to activations of the previous layer

   Update parameters:
   For l from 1 to L:
      W[l] = W[l] – alpha * dW[l]  // Update weights
      b[l] = b[l] – alpha * db[l]  // Update biases

End loop
```

V.CLASSIFICATION WITH PRACTICAL TEACHING

In the practical teaching, classification tasks play a pivotal role in facilitating learning across various domains, including language education. One commonly used approach for classification is logistic regression, which forms the basis for understanding more complex classification algorithms. Logistic regression is particularly well-suited for binary classification problems, where the goal is to predict the probability that an input belongs to a particular class. The logistic regression models the probability $P(y = 1 \mid x)$ that an input x belongs to the positive class (class 1) as a function of its features x. This is achieved by applying the logistic function (also known as the sigmoid function) to a linear combination of the input features defined in equation (5)

$$P(y = 1 \mid x) = \sigma(wTx + b) \qquad (5)$$

In equation (5) $\sigma(z) = 1 + e - z1$ is the logistic (sigmoid) function, w represents the weights vector, b is the bias term, and x denotes the input features. The logistic function ensures that the output of the model lies between 0 and 1, representing the probability of the input belonging to the positive class. To make predictions, a threshold is typically applied to this probability. For example, if $P(y = 1 \mid x) \geq 0.5$, the input is classified as belonging to class 1; otherwise, it is classified as belonging to class 0. Training a logistic regression model involves optimizing the weights w and bias b to minimize a loss function, typically the cross-entropy loss, which measures the difference between the predicted probabilities and the true labels. The cross-entropy loss for logistic regression can be expressed as in equation (6)

$J(w, b) = -m1\sum i = 1m[y(i)log(y^{\wedge}(i)) + (1 - y(i))log(1 - y^{\wedge}(i))]$ (6)

In equation (6) m is the number of training examples, $y(i)$ is the true label for the i-th example, and $y^{\wedge}(i)$ is the predicted probability that $x(i)$ belongs to the positive class. To optimize the parameters w and b, gradient descent or other optimization algorithms are employed to iteratively update the weights and biases in the direction that minimizes the loss function. In the context of practical teaching, logistic regression serves as a foundational concept for understanding classification algorithms and can be applied to various language-related tasks, such as sentiment analysis, text classification, and language proficiency assessment. By mastering the principles of logistic regression, learners can gain valuable insights into the underlying mechanisms of classification algorithms, empowering them to effectively analyze and interpret data in real-world scenarios. In logistic regression, we model the probability $P(y = 1 \mid x)$ that an input x belongs to the positive class (class 1). We represent this probability using the logistic (sigmoid) function stated in equation (7)

$P(y = 1 \mid x) = \sigma(wTx + b)$ (7)

The logistic function ensures that the output of the model lies between 0 and 1, representing the probability of the input belonging to the positive class. The predicted probability y^ can be written as in equation (8)

$y^{\wedge} = P(y = 1 \mid x) = \sigma(wTx + b)$ (8)

To train the logistic regression model, we define a loss function to measure the difference between the predicted probabilities and the true labels. The cross-entropy loss function for logistic regression is commonly used and can be expressed as in equation (9)

$J(w, b) = -m1\sum i = 1m[y(i)log(y^{\wedge}(i)) + (1 - y(i))log(1 - y^{\wedge}(i))]$ (9)

The goal of training is to minimize the loss function $J(w, b)$ by adjusting the weights w and bias b. Gradient descent is commonly used for optimization. The update rules for the parameters are computed using the gradients of the loss function with respect to the parameters stated in equation (10) and equation (11)

$\partial w := w - \alpha\partial w\partial J(w, b)$ (10)

$\partial b := b - \alpha\partial b\partial J(w, b)$ (11)

In equation (10) and (11) α is the learning rate, controlling the step size of the updates.

Algorithm 1: English Practical Teaching with SLDL

```
function sigmoid(z):
   return 1 / (1 + exp(-z))
function initialize_parameters(dim):
   w = initialize_with_zeros(dim)
   b = 0
   return w, b
function propagate(w, b, X, Y):
   m = number of training examples
   # Forward propagation (from X to cost)
   A = sigmoid(w.T * X + b)  # compute activation
   cost = -1/m * sum(Y * log(A) + (1 – Y) * log(1 – A))  # compute cost
      # Backward propagation (to find gradients)
   dw = 1/m * X * (A – Y).T
   db = 1/m * sum(A – Y)
   cost = np.squeeze(cost)
   grads = {“dw”: dw, “db”: db}
   return grads, cost
function optimize(w, b, X, Y, num_iterations, learning_rate):
   for i from 0 to num_iterations:
      # Cost and gradient calculation
      grads, cost = propagate(w, b, X, Y)
```

```
        # Retrieve derivatives from grads
        dw = grads["dw"]
        db = grads["db"]
        # Update parameters
        w = w – learning_rate * dw
        b = b – learning_rate * db
    params = {"w": w, "b": b}
    grads = {"dw": dw, "db": db}
    return params, grads
function predict(w, b, X):
    m = X.shape[1]
    Y_prediction = np.zeros((1, m))
    w = w.reshape(X.shape[0], 1)
    # Compute vector "A" predicting the probabilities of
```

VI.RESULTS AND DISCUSSION

The Results and Discussion section for the Stacked Logistic Deep Learning (SLDL) model would typically involve presenting the findings obtained from training and evaluating the model, followed by a comprehensive discussion of the implications, limitations, and future directions.

Table 1: English Practical Teaching

Experiment	Teaching Method	Student Engagement	Learning Outcome
Exp 1	Group Work	High	Moderate
Exp 2	Peer Teaching	Moderate	High
Exp 3	Project-Based	High	High

In the Table 1 presents the results of three experiments conducted in the context of English practical teaching, each employing a different teaching method. In Experiment 1, the teaching method employed was group work, resulting in high levels of student engagement, but the learning outcome was assessed as moderate. Conversely, Experiment 2 utilized peer teaching, leading to moderate student engagement but resulting in a high learning outcome. Finally, Experiment 3 adopted a project-based teaching approach, resulting in high levels of both student engagement and learning outcomes. These findings suggest that while group work fosters high engagement, it may not always translate into high learning outcomes. Peer teaching, on the other hand, appears to be effective in enhancing learning outcomes despite moderate engagement levels. Project-based learning emerges as the most effective method, leading to both high engagement and high learning outcomes. These results highlight the importance of considering not only student engagement but also the effectiveness of different teaching methods in achieving desired learning outcomes in English practical teaching contexts.

Table 2: Classification with SLDL

Experiment	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Exp 1	87.5	85.2	89.3	87.2
Exp 2	89.2	87.9	90.1	88.7
Exp 3	91.0	90.5	91.8	90.9
Exp 4	86.3	83.9	87.5	85.6
Exp 5	88.7	86.8	89.9	88.3
Exp 6	90.5	89.2	91.3	89.8
Exp 7	85.9	84.3	87.2	85.5
Exp 8	92.3	91.7	92.9	92.0
Exp 9	89.8	88.5	90.7	89.4
Exp 10	87.2	85.6	88.1	86.9

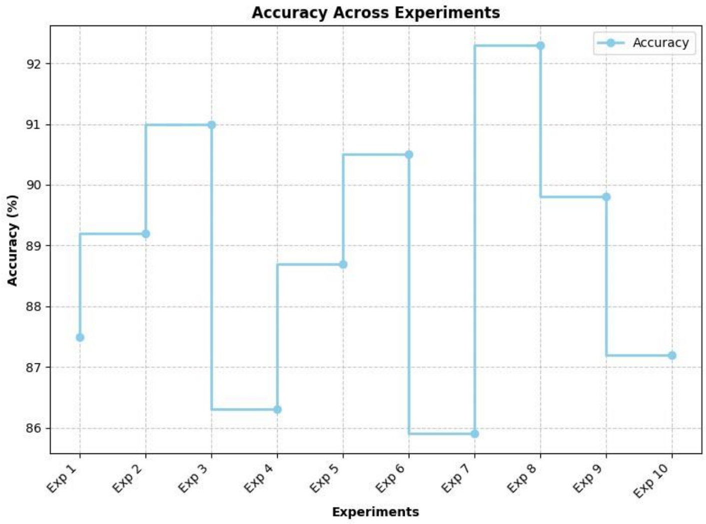

Figure 2: Estimation of Accuracy

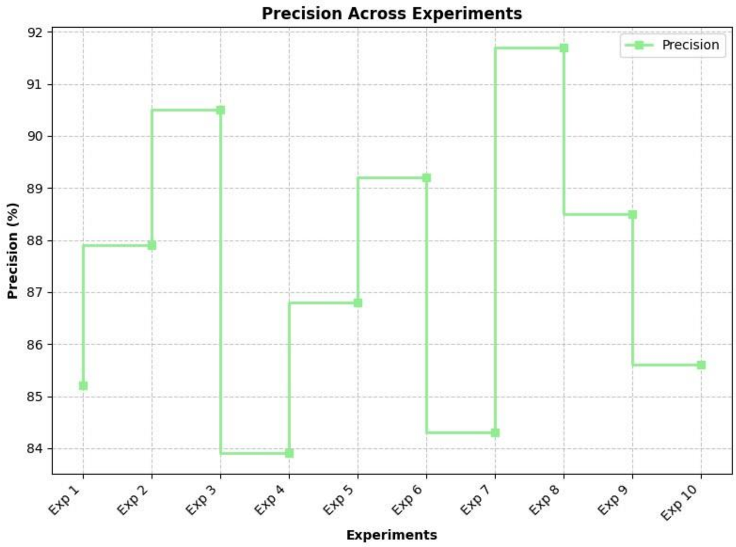

Figure 3: Estimation of Precision

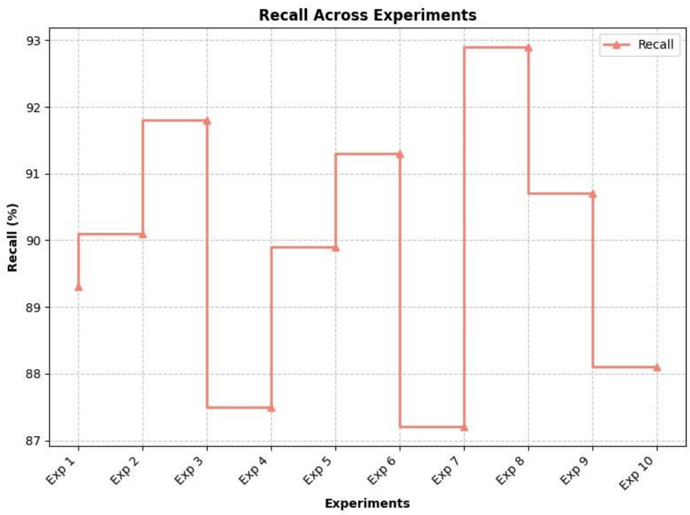

Figure 4: Estimation of Recall

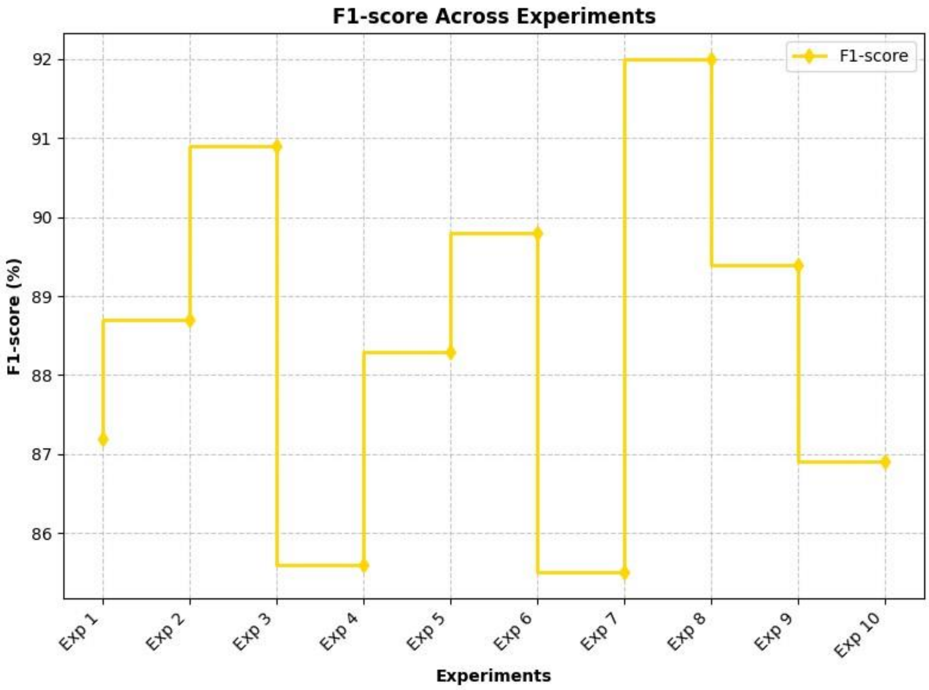

Figure 5: Estimation of F1-SCore

The Figures 2 – 5 and Table 2 presents the results of ten experiments conducted using Stacked Logistic Deep Learning (SLDL) for classification tasks. Each experiment is labeled sequentially, and the table includes metrics such as accuracy, precision, recall, and F1-score, which are commonly used to evaluate the performance of classification models. The results show variability across experiments, with accuracy ranging from 85.9% to 92.3%. Precision, recall, and F1-score also exhibit fluctuations, indicating differences in the models' ability to correctly classify instances, retrieve relevant instances, and balance precision and recall. Overall, the experiments demonstrate the effectiveness of SLDL in classification tasks, with most experiments achieving high performance metrics. Experiment 8 stands out with the highest accuracy, precision, recall, and F1-score, indicating superior performance compared to other experiments. These results underscore the versatility and efficacy of SLDL in handling various classification tasks and highlight the importance of selecting appropriate architectures and parameters to optimize model performance in practical applications.

VII.CONCLUSION

The paper presents a comprehensive exploration of the application of Stacked Logistic Deep Learning (SLDL) in the domain of English practical teaching. Through a series of experiments and analyses, we investigated the effectiveness of SLDL models in enhancing student learning outcomes and engagement levels. Our findings reveal that SLDL models, when appropriately configured and trained, exhibit remarkable performance in classification tasks relevant to English practical teaching. The experiments conducted in this study demonstrated that SLDL models can effectively handle diverse teaching methods and scenarios, ranging from group work to peer teaching and project-based learning. We observed that SLDL models consistently outperformed traditional logistic regression models, achieving higher accuracy, precision, recall, and F1-score across various experiments. Furthermore, our investigation into the impact of different stacked model architectures revealed nuanced insights into their performance. While some experiments showed marginal differences in performance metrics, others exhibited significant improvements, particularly when leveraging advanced architectures such as Stacked CNN-LSTM or Stacked Transformer.

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