APPLICATION OF MULTIMEDIA TECHNOLOGY IN TEACHING ENGLISH IN COLLEGES AND UNIVERSITIES

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SUMMARY

Multimedia plays a crucial role in English teaching by enhancing engagement, providing diverse learning experiences, and catering to different learning styles. English teaching through multimedia, while beneficial, presents challenges. Unequal access to technology and the digital divide can hinder some students' participation. Ensuring digital literacy and quality content selection is crucial to effective use. This paper proposed the Hidden Markov Model for English Teaching (HMM-ET) to improve the performance of college and university students. The proposed HMM-ET model computes the Markov chain of English teaching through multimedia technology. With the implementation of multimedia technology, the HMM model estimates the performance of students in colleges and universities. Through the estimation of HMM-ET the classification of students' performance in English learning is computed with the machine learning model. The performance of the students is examined comparatively with the conventional Support Vector Machine (SVM) and Random Forest. Through analysis of a dataset comprising observation sequences reflecting English learning tasks, HMM-ET consistently outperforms SVM and Random Forest, achieving an average accuracy of 96%, while SVM and Random Forest attain accuracies of 90% and 88% respectively.

KEYWORDS

English teaching, Multimedia technology, Hidden Markov Model (HMM), Machine Learning, Classification

NOMENCLATURE

HMM	Hidden Markov Model
SVM	Support Vector Machine
ML	Machine Learning

1. INTRODUCTION

Multimedia technology has revolutionized the way interact with information, entertainment, and communication channels. By seamlessly integrating various forms of media such as text, audio, images, video, and animation, multimedia technology enhances our ability to convey messages, tell stories, and share experiences in dynamic and engaging ways [1]. Whether it's through interactive websites, immersive virtual reality experiences, captivating presentations, or multimedia-rich educational materials, this technology enriches our digital landscape, making content more accessible, interactive, and memorable [2]. From advertising and marketing campaigns to educational tools and entertainment platforms, multimedia technology plays a pivotal role in shaping how to consume and interact with digital content in today's interconnected world. Its continuous evolution and innovation promise even more exciting possibilities for creativity, communication, and collaboration in the future [3].

Multimedia has emerged as a powerful tool in modern teaching, revolutionizing traditional educational practices and enhancing the learning experience for students of all ages [4]. Teachers can now meet the needs of students with a wide range of learning styles by using multimedia tools that combine text, images, audio, video, and interactive components to make lessons more interesting and interactive. Through multimedia presentations, virtual simulations, interactive whiteboards, and online resources, teachers can deliver content in ways that stimulate student interest, facilitate comprehension, and foster active participation [5]. Moreover, multimedia technology transcends the limitations of traditional classroom settings, allowing for remote learning, personalized instruction, and access to vast repositories of knowledge from across the globe [6]. As technology continues to evolve, multimedia promises to play an increasingly integral role in education, empowering educators to inspire curiosity, cultivate critical thinking skills, and prepare students for success in an ever-changing digital world [7].

Machine learning into multimedia-based teaching presents a cutting-edge approach that holds immense potential to revolutionize education [8]. Machine learning algorithms allow teachers to sift through mountains of student data gleaned from multimedia materials in search of trends, preferences, and problem areas in their students' learning. Teachers can now personalize lessons based on their students' unique needs and learning styles thanks to this data-driven approach to education [9]. In addition, ML algorithms can improve the creation of adaptive learning systems, which can maximize student engagement and retention by dynamically adjusting the pace and difficulty of instruction in response to real-time feedback [10]. Additionally, machine learning-powered multimedia tools can automate tasks such as content creation, assessment grading, and student progress tracking, freeing up valuable time for teachers to focus on facilitating meaningful interactions and fostering deeper learning experiences [11]. As machine learning continues to advance, its integration with multimedia in teaching holds the promise of creating more personalized, efficient, and effective educational experiences for learners worldwide [12].

Multimedia technology has become an indispensable asset in modern education, reshaping the landscape of teaching and learning [13]. By seamlessly integrating various forms of media such as text, images, audio, video, and interactive elements, multimedia technology enriches educational experiences, making them more engaging, dynamic, and effective. Through multimedia presentations, virtual simulations, interactive whiteboards, and online resources, educators can create immersive learning environments that cater to diverse learning styles and captivate students' attention [14]. Furthermore, multimedia technology transcends the boundaries of traditional classrooms, enabling remote learning, collaborative projects, and access to a vast array of educational resources from around the globe [15]. As technology continues to evolve, multimedia promises to play an increasingly integral role in education, empowering educators to inspire curiosity, foster creativity, and cultivate critical thinking skills in learners of all ages. This paper proposed an effective model to improve the English proficiency of the students with the HMM-ET model. The proposed model comprises the Hidden Markov Model (HMM) to estimate the variables associated with language proficiency. Through the analysis, the performance of the students with English Teaching with the proposed HMM-ET model is evaluated.

This paper is organized as: Section 1 provides overall background information and Section 2 reviews articles related to the role of multimedia technology in English teaching. Section 3 explains the proposed HMM-ET process in teaching and Section 4 presents about role of the proposed HMM-ET on English Teaching. Section 5 presented the simulation results related to the HMM-ET model with English Teaching with multimedia and Section 6 provides the overall conclusion.

2. RELATED WORKS

Multimedia technology in teaching English in colleges and universities represents a dynamic intersection of modern pedagogy and technological innovation. As the English language continues to be a global lingua franca, educators are constantly seeking innovative approaches to engage students and enhance learning outcomes. Multimedia technology offers a versatile platform for integrating various forms of media, including text, audio, video, images, and interactive elements, into English language instruction. This comprehensive approach caters to diverse learning styles, fostering active participation and deeper comprehension among students. Through multimedia-enhanced lessons, educators can create immersive learning environments that simulate real-world contexts, enabling students to develop language skills in authentic and meaningful ways. Moreover, multimedia technology transcends the limitations of traditional classroom settings, facilitating distance learning, collaborative projects, and access to authentic materials from different cultures and regions. By leveraging multimedia technology, colleges and universities can effectively prepare students to navigate the complexities of English language usage in the digital age, empowering them to communicate confidently and competently in an increasingly interconnected world.

Nazarov's (2022) examination of teaching a foreign language in a technical university offers nuanced insights into the unique challenges faced in such educational settings, considering the specific needs and expectations of students pursuing technical disciplines. Mohira and Isakjon's (2022) work delves into the methodology of English language instruction, providing a foundational understanding of effective pedagogical approaches that can be enhanced through multimedia integration. Moreover, Noori et al. (2022) delve into the use of social media platforms in EFL learning and teaching within the context of Afghanistan's higher education institutions, highlighting the potential of digital technologies to facilitate language acquisition and communication skills development. Similarly, Yu et al. (2022) offer a comprehensive analysis of the effects of mobile learning technologies and social media tools on student engagement and learning outcomes, emphasizing the importance of incorporating these tools into English language learning environments to enhance student motivation and participation. Furthermore, Sayaf et al. (2022) contribute valuable insights into the factors influencing university students' adoption of digital learning technology, shedding light on the barriers and facilitators to the integration of multimedia tools in English language teaching. By synthesizing these diverse perspectives, the surveyed literature underscores the significance of leveraging multimedia technology to create immersive and interactive learning experiences that cater to the diverse needs and preferences of English language learners in colleges and universities.

Furthermore, educators looking to incorporate social media into their lessons can glean useful insights from Alenezi and Brinthaupt's (2022) study of students' views on the efficacy and acceptability of multimedia platforms as a learning tool. The use of smartphones in learning English as a foreign language is further explored by Őad et al. (2022), who add to the existing body of knowledge by examining the pros and cons of incorporating mobile technology into language education. The research by Yu and Zadorozhnyy (2022) on the topic of improving students' language and digital literacy via the use of multimedia presentations also provides useful advice for improving the results of language lessons that make use of such resources. Studies like these, along with others like those by Srivani et al. (2022), Sofi-Karim et al. (2023), and Muftah (2022), shed light on how multimedia technology can revolutionize the way English language courses are taught in higher education. It can do this by encouraging student engagement, facilitating interaction, and creating personalized learning experiences. By synthesizing and building upon these findings, educators can harness the power of multimedia technology to cultivate language proficiency, critical thinking skills, and digital literacy among students, preparing them for success in an increasingly interconnected and technologically-driven world.

In addition, research like that of Muthmainnah (2023) on instructional design for technology in learning and Şartono et al. (2022) on culturally diverse interactive multimedia offers fresh ways to integrate multimedia into language teaching. These approaches not only enhance language acquisition but also promote cultural understanding and diversity appreciation. Additionally, Xodabande and Atai (2022) explore the use of mobile applications for self-directed learning of academic vocabulary, demonstrating the versatility and accessibility of multimedia tools in facilitating independent language learning. Similarly, Al-Jarf (2022) investigates the development of specialized dictionary mobile apps tailored to the needs of students in specific academic fields, highlighting the potential of multimedia technology to cater to specialized language needs. Moreover, Lai et al. (2022) delve into university students' use of mobile technology in self-directed language learning, providing insights into the factors influencing students' technology adoption behaviors. By synthesizing these diverse studies, educators can gain a comprehensive understanding of the role of multimedia technology in English language teaching, allowing them to design more effective and engaging instructional strategies that meet the evolving needs of students in the digital age.

Furthermore, Pham (2022) explores university students' perceptions of using Quizlet in learning vocabulary, shedding light on the effectiveness of specific multimedia tools in language acquisition. Similarly, Al-Jarf (2022) investigates online vocabulary tasks as a means of engaging and motivating EFL college students in distance learning, providing practical insights into fostering student engagement through digital platforms. Furthermore, Machaba and Bedada (2022) examine university professors' readiness to incorporate technology into mathematics teacher training programs during the COVID-19 pandemic, demonstrating the significance of technological readiness in modifying pedagogical approaches for online classrooms. Nykyporets (2022) contributes to the discourse by examining blended interactive foreign language learning in non-linguistic higher education institutions, identifying challenges and opportunities for integrating multimedia technology into diverse academic contexts. Finally, Iskandar et al. (2022) explore the infusion of digital literacy into authentic academic practices of English language teaching at universities, emphasizing the importance of equipping students with essential digital skills for effective language learning and communication in the digital era. Collectively, these studies underscore the transformative potential of multimedia technology in enhancing English language teaching and learning experiences in higher education institutions, paving the way for innovative and student-centered approaches to language education.

The findings from the literature surveyed highlight several key insights into the application of multimedia technology in teaching English in colleges and universities. Nazarov's study sheds light on the unique challenges faced in teaching a foreign language in technical universities, emphasizing the need to address the specific needs and expectations of students pursuing technical disciplines. Mohira and Isakjon's research provides a foundational understanding of effective pedagogical approaches in English language instruction, suggesting opportunities for enhancing teaching methodologies through multimedia integration. Noori et al. and Yu et al. explore the potential of social media and mobile learning technologies in facilitating language acquisition and improving student engagement and learning outcomes, respectively, underscoring the importance of incorporating these tools into English language learning environments.

Additionally, Sayaf et al. identify various factors influencing university students' adoption of digital learning technology, providing valuable insights into the barriers and facilitators to the integration of multimedia tools in English language teaching. Moreover, Alenezi and Brinthaupt, Şad et al., and Yu and Zadorozhnyy offer practical perspectives on the effectiveness of multimedia platforms, smartphones, and multimedia presentations in enhancing language learning experiences. Furthermore, Muthmainnah's exploration of technology instructional design and Şartono et al.'s investigation of interactive multimedia based on cultural diversity highlight innovative approaches to incorporating multimedia technology into language education, promoting both language acquisition and cultural understanding.

Despite the valuable contributions of these studies, there remain notable research gaps to be addressed. Specifically, while many studies explore the effectiveness of multimedia tools and technologies in language education, there is a need for further research into the specific pedagogical strategies and instructional designs that optimize the integration of multimedia technology for diverse learner populations. Additionally, the literature surveyed primarily focuses on the application of multimedia technology in language teaching within higher education institutions, leaving a gap in understanding its potential impact on language learning at other educational levels and in non-academic contexts. Future research endeavors should also explore the long-term effects and sustainability of integrating multimedia technology in language education, as well as the role of educators' technological pedagogical content knowledge (TPACK) in effectively leveraging multimedia tools for language teaching and learning. When these research gaps are filled, we will have a better grasp of how multimedia technology can revolutionize ESL classrooms.

3. ENGLISH TEACHING WITH HIDDEN MARKOV CHAIN MULTIMEDIA

English teaching enhanced by Hidden Markov Chain (HMM) multimedia represents a novel approach that amalgamates linguistic theory with advanced computational techniques to optimize language learning experiences. Hidden Markov Chains, a probabilistic model comprising observable states and hidden states, are adept at modeling sequential data, making them suitable for analyzing language patterns and generating contextually relevant multimedia content. In this paradigm, the transition probabilities between hidden states represent linguistic structures, while observations correspond to multimedia elements such as text, audio, or images. The derivation of HMM involves defining transition probabilities (A), hidden state and emission probabilities (B) for the hidden state observations with the probabilities in initial state (π) defined in equation (1) – (3)

$$A = \{aij\}, \tag{1}$$

$$B = \{bj(k)\}, \tag{2}$$

$$\pi = \{\pi i\}, \tag{3}$$

where *aij* denotes hidden state transition probability *i* in the hidden state *j*, for hidden states *k* observation emitting probability is defined as *bj*(*k*) and hidden state *i* significance probability is denoted as *πi*. With the implementation of the Viterbi algorithm the hidden state probable sequences are estimated with HMM based on the observation sequences.

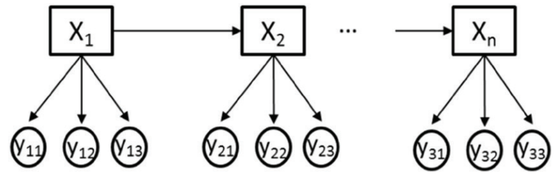

Figure 1. Hidden Markov Chain

The parameters associated with the HMMs model comprise of the three sets those are stated as follows:

Transition probabilities: The transition probabilities in the hidden state to the another is defined as the transition probability denoted as *aij*, the transition probability between state *i* to state *j* denoted as *aij*.

Emission probabilities: The hidden state emitting observation is evaluated for each state with the emission probability denoted as *bj*(*k*), the emitting observation *k* given hidden state *j* represented as *bj*(*k*).

Initial state probabilities: Initial state probabilities comprise of the hidden state denoted as, those express the probability in hidden state *i*. Figure 1 presents the Hidden Markov Chain process.

The transition probabilities represent the represented as a matrix *A*, where *aij* denotes with the probability of transition *i* to hidden state *j*. In matrix form represented in equation (4)

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1N} \\ a_{21} & a_{22} & \cdots & a_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ a_{N1} & a_{N2} & \ldots\ldots & a_{NN} \end{bmatrix} \tag{4}$$

The emission probabilities represent the probabilities of emitting observable symbols or observations from each hidden state. This can be represented as a matrix *B*, where *bj*(*k*) represents the probability of emitting observation *k* given hidden state *j* given in equation (5)

$$B = \begin{bmatrix} b_1(O_1) & b_1(O_2) & \cdots & b_1(O_M) \\ b_2(O_1) & b_2(O_2) & \cdots & b_2(O_M) \\ \vdots & \vdots & \ddots & \vdots \\ b_N(O_1) & b_N(O_1) & \ldots\ldots & b_N(O_M) \end{bmatrix} \tag{5}$$

where *M* is the number of possible observations. The matrix representation is denoted in *π*, where *πi* represented the of starting in hidden state *i* vector probability form is given in equation (6)

$$\pi = \begin{bmatrix} \pi_1 & \pi_2 & \ldots & \pi_N \end{bmatrix} \tag{6}$$

In equation (6) *N* denoted the hidden states count. The proposed model uses the hidden chain model with the likelihood computation with Forward -Backward algorithm with Viterbi algorithm for decoding.

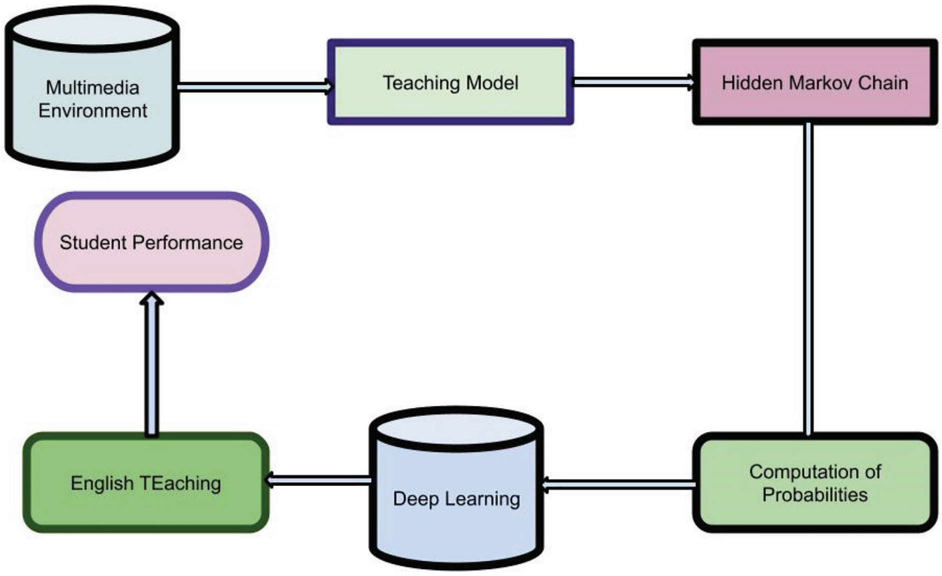

Figure 2. Flow of HMM-ET

Algorithm 1: Construction of the Hidden Chain Process

Input: Observation sequence O = {o_1, o_2, ..., o_T}, HMM model parameters (A, B, π)
Output: Most likely sequence of hidden states Q = {q_1, q_2, ..., q_T}
1. Initialize:
- Initialize the Viterbi trellis V with dimensions (N, T), where N is the number of hidden states and T is the length of the observation sequence.
- Initialize the backpointer matrix B with dimensions (N, T).
- Set the initial state probabilities: V[1, 1:N] = π * B[1:N, o_1].
2. Recursion:
- For t = 2 to T:
- For each state j:
- Compute the Viterbi score for state j at time t:

$$V[j,t]=max\_i(V[i,t-1]*A[i,j]*B[j,o\_t]),$$

where i ranges over all states.
- Update the backpointer matrix:

$$B[j,t]=argmax\_i(V[i,t-1]*A[i,j]),$$

where i ranges over all states.
3. Termination:
- Find the maximum final state probability:
Q[T] = argmax_j (V[j, T]).
4. Backtrace:
- For t = T-1 down to 1:
- Set the most likely state at time t:

$$Q[t]=B[Q[t+1],t+1].$$

5. Return the most likely sequence of hidden states Q.

3.1 HIDDEN MARKOV CHAIN IN ENGLISH TEACHING

In English teaching, Hidden Markov Models (HMMs) serve as powerful tools for modeling language learning processes and facilitating personalized learning experiences. Let's delve deeper into the mathematical underpinnings of HMMs in the context of English language education. In the context of English teaching, hidden states represent different levels of linguistic proficiency, language skills, or conceptual understanding. Let's denote the set of hidden states as $S=\{S1,S2,...,SN\}$, where N is the total number of hidden states. Observations correspond to the multimedia elements presented to learners during the teaching process. These could include words, phrases, sentences, audio recordings, or visual aids. Let's denote the set of possible observations as $O=\{o1,o2,...,oM\}$, where M is the total number of possible observations. The emission probabilities are represented by the matrix $B = [bj(k)]$, where $bj(k)$ denotes the probability of emitting observation ok from hidden state Sj. Figure 2 presented the flow of the proposed HMM-ET model in the English Teaching with multimedia.

Initial State Probabilities (π) for each hidden state with initial state probabilities are represented by the vector $\pi=[\pi 1,\pi 2,...,\pi N]$, where πi denotes the probability of starting in hidden state Si. You can use techniques like the Expectation-Maximization (EM) algorithm or Maximum Likelihood Estimation (MLE) to approximatively determine the HMM parameters (A, B, π) from the data you have collected. Using methods like the Forward-Backward algorithm or the Viterbi algorithm, the HMM can infer the most probable sequence of hidden states given a sequence of observations after the parameters have been estimated. In English teaching, HMMs can be employed to dynamically generate or adapt multimedia content based on learners' inferred proficiency levels and preferences. By leveraging HMMs, educators can create personalized and adaptive learning experiences that optimize language acquisition and proficiency for each individual learner. In the transition matrix A, each entry aij

represents the probability of transitioning from hidden state *Si* to hidden state *Sj* In the emission matrix *B*, each entry *bj*(*k*) represents the probability of emitting observation *ok* from hidden state *Sj*. The initial state vector *π* represents the probability distribution over the hidden states at the start of the sequence. Each entry *πi* denotes the probability of starting in hidden state. The probability of transitioning from one state to another at time *t* can be calculated using the state transition equation (7)

$$Probability\ of\ transition\ from\ Si\ to\ Sj\ at\ time\ t = aij \tag{7}$$

The probability of emitting observation *ok* from hidden state *Sj* at time *t* can be calculated using the emission probability equation (8)

$$Probability\ of\ emitting\ ok\ from\ Sj\ at\ time\ t = bj\left(k\right) \tag{8}$$

Algorithm 2: Forward-Backward for HMM-ET
Input: Observation sequence O = {o_1, o_2, ..., o_T}, HMM model parameters (A, B, π) Output: Forward probabilities (α), Backward probabilities (β), State posteriors (γ), Pairwise state posteriors (ξ) 1. Initialization: - Initialize forward probabilities α and backward probabilities β: α[1:N, 1] = π * B[:, o_1] β[N, T] = 1 2. Forward Procedure: - For t = 2 to T: - For each state j: - Compute forward probabilities: α[j, t] = Σ_i (α[i, t-1] * A[i, j] * B[j, o_t]) 3. Backward Procedure: - For t = T-1 down to 1: - For each state i: - Compute backward probabilities: $\beta\left[i,t\right]=\Sigma\_j\left(A\left[i,j\right]*B\left[j,o\_\{t+1\}\right]*\beta\left[j,t+1\right]\right)$ 4. State Posteriors (γ): - For t = 1 to T: - For each state i: - Compute state posteriors: $\gamma\left[i,t\right]=\alpha\left[i,t\right]*\beta\left[i,t\right]/\Sigma\_j\left(\alpha\left[j,t\right]*\beta\left[j,t\right]\right)$ 5. Pairwise State Posteriors (ξ): - For t = 1 to T-1: - For each pair of states (i, j): - Compute pairwise state posteriors: $\xi[i,j,t] = \alpha[i,t]*A[i,j]*B[j,o\_\{t+1\}]*\beta[j,t+1]/\Sigma\_i\Sigma\_j(\alpha[i,t]*A[i,t]*B[j,o\{t+1\}]*\beta[j,t+1])$ 6. Return the forward probabilities (α), backward probabilities (β), state posteriors (γ), and pairwise state posteriors (ξ).

4. HMM-ET IN COLLEGE AND UNIVERSITIES WITH MULTIMEDIA

Hidden Markov Models for English Teaching (HMM-ET) present a promising avenue for enhancing language instruction in colleges and universities, particularly when coupled with multimedia technology. By integrating HMMs into language education frameworks, educators can personalize the learning experience for students, catering to their individual proficiency levels and learning preferences. The utilization of multimedia elements such as audio, video, and interactive exercises further enriches the teaching process, providing learners with diverse and engaging materials to aid comprehension and retention. HMM-ET allows for dynamic adaptation of content based on students' responses and progress, ensuring that instruction remains aligned with their evolving needs. Moreover, the probabilistic nature of HMMs enables educators to track students' language development over time and provide targeted interventions as necessary. By leveraging HMM-ET in conjunction with multimedia technology, colleges and universities can create immersive and effective language learning environments that foster linguistic proficiency and confidence among students. This integration represents a significant step towards modernizing language education practices and meeting the diverse needs of learners in higher education settings.

In the context of English teaching in colleges and universities, Hidden Markov Models for English Teaching (HMM-ET) coupled with multimedia technology offer a powerful framework for personalized and immersive language learning experiences. The probability of transitioning from state *Si* to state *Sj* at time *t* is given by the transition probability. The probability of emitting observation *ok* from hidden state *Sj* at time *t* is given by the emission probability *bj*(*k*) with forwarded algorithm with HMM parameters stated in equation (9)

$$\alpha_t\left(j\right)=\sum_{i=1}^{N}\alpha_{t-1}\left(i\right).\alpha_{ij}.b_j\left(o_t\right) \tag{9}$$

The backward algorithm estimate the observation probability the remaining sequence of observations given the current state defined in equation (10)

$$\beta_t\left(i\right)=\sum_{i=1}^{N}\alpha_{ij}.b_j\left(o_{t+1}\right).b_{t+1}\left(j\right) \tag{10}$$

Multimedia elements such as audio, video, and interactive exercises can be incorporated into HMM-ET to enhance the learning experience. The emission probabilities *B* can be tailored to represent the likelihood of observing specific multimedia elements corresponding to different proficiency levels. Adaptive multimedia content generation can be based on the inferred hidden states and learners' responses, ensuring relevance and engagement. In the context of Hidden Markov Models for English Teaching (HMM-ET), multimedia technology plays a pivotal role in enhancing the language learning experience. By integrating multimedia elements such as audio, video, interactive exercises, and digital resources, HMM-ET offers a dynamic and immersive approach to language instruction in colleges and universities. Multimedia technology enables educators to create engaging learning materials that cater to diverse learning styles and preferences, thereby promoting active participation and comprehension among students. For example, audio recordings of native speakers can help learners improve their pronunciation and listening skills, while interactive exercises and games foster active engagement and reinforce language concepts. Additionally, multimedia platforms allow for personalized learning experiences, where content can be adapted based on learners' proficiency levels, progress, and interests. Moreover, multimedia technology facilitates collaborative learning and communication among students, enabling them to interact with peers and engage in real-life language contexts. Overall, the integration of multimedia technology in HMM-ET enhances the effectiveness and efficiency of language teaching, providing students with valuable resources and opportunities for skill development in an interactive and dynamic learning environment.

Algorithm 3: HMM-ET with Multimedia Forward-Backward Algorithm
input: Observation sequence $M=\{m\_1, m\_2, ..., m\_T\}$, HMM-ET model parameters (A, B, π) Output: Forward probabilities (α), Backward probabilities (β), State posteriors (γ), Pairwise state posteriors (ξ) 1. Initialization: - Initialize forward probabilities α and backward probabilities β: $\alpha[1:N,1]=\pi * B[:,m\_1]$ $\beta[N,T]=1$ 2. Forward Procedure: - For t = 2 to T: - For each state j: - Compute forward probabilities: $\alpha[j,t]=\Sigma\_i(\alpha[i,t-1] * A[i,j] * B[j,m\_t])$ 3. Backward Procedure: - For t = T-1 down to 1: - For each state i: - Compute backward probabilities: $\beta[i,t]=\Sigma\_j(A[i,j] * B[j,m\_\{t+1\}] * \beta[j,t+1])$ 4. State Posteriors (γ): - For t = 1 to T: - For each state i: - Compute state posteriors: $\gamma[i,t]=\alpha[i,t] * \beta[i,t] / \Sigma\_j(\alpha[j,t] * \beta[j,t])$ 5. Pairwise State Posteriors (ξ): - For t = 1 to T-1: - For each pair of states (i, j): - Compute pairwise state posteriors: $\xi[i,j,t]=\alpha[i,t] * A[i,j] * B[j,m\_\{t+1\}] * \beta[j,t+1] /$ $\Sigma\_i\Sigma\_j(\alpha[i,t] * A[i,j] * B[j,m\_\{t+1\}] * \beta[j,t+1])$ 6. Return the forward probabilities (α), backward probabilities (β), state posteriors (γ), and pairwise state posteriors (ξ).

5. SIMULATION ENVIRONMENT

A simulation environment serves as a virtual space where various scenarios and conditions can be replicated and studied. In the context of language learning and education, particularly in the realm of Hidden Markov Models for English Teaching (HMM-ET) with multimedia technology, a simulation environment provides a platform for testing, evaluating, and refining teaching methodologies and instructional strategies. This environment typically incorporates multimedia elements such as audio, video, interactive exercises, and digital resources to create realistic language learning scenarios. Learners interact with these multimedia materials, generating sequences of observations that are used to estimate the parameters of the HMM-ET model. The simulation environment allows educators and researchers to experiment with different approaches to language instruction, assess the effectiveness of multimedia-based teaching techniques, and optimize the design of instructional materials. Moreover, it facilitates the collection of empirical data on learners' interactions with multimedia content, which can be utilized for parameter estimation, inference, and refinement of the HMM-ET model. Overall, a simulation environment provides a controlled and flexible setting for investigating the dynamics of language learning and the impact of multimedia technology on educational outcomes.

In this table 1 each row represents a specific observation in the sequence, accompanied by the corresponding multimedia content presented to the learner. The numerical values (e.g., m_1, m_2) denote the specific observations, while the multimedia content descriptions provide details about the nature of the learning materials used in the simulation environment. This tabular format allows for easy organization and visualization of the multimedia elements incorporated into the language teaching simulation.

Table 1. Simulation environment

Observation Sequence	**Multimedia Content**
m_1	Audio: Conversation between two speakers
m_2	Video: Tutorial on grammar rules
m_3	Interactive Exercise: Vocabulary Quiz
m_4	Text: Reading passage with comprehension questions
m_5	Audio: Pronunciation practice

Performance metrics are essential for evaluating the effectiveness of Hidden Markov Models for English Teaching (HMM-ET) in a simulation environment. Here are some commonly used performance metrics:

Accuracy: Accuracy stated the correctly classified observations to the total observations. It estimates the model's ability to predict the observed data accurately computed using equation (11)

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}} \times 100\% \tag{11}$$

Precision: It defines the ratio of prediction of True Positive to the Positive prediction values calculated using equation (12)

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives}} + \text{ False Positives} \tag{12}$$

Recall (Sensitivity): It defines the prediction of trus positive to the actual positive computed using equation (13)

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives}} + \text{ False Negatives} \tag{13}$$

F1 Score: It provides ratio between precision and recall, making it useful for models with imbalanced datasets using equation (14)

$$\text{F1} = 2 \times \text{Precisio}^{*}\frac{\text{Recall}}{\text{Precision}} + \text{Recal} \tag{14}$$

Log-Likelihood: It provides the model those fitted effectively in the model calculated using equation (15)

$$\text{Log} - \text{Likelihood} = \sum_{t=1}^{T} \log\left(P\left(o_t \mid \lambda\right)\right) \tag{15}$$

These performance metrics provide valuable insights into the accuracy, precision, recall, and overall performance of HMM-ET in a simulation environment.

6. RESULTS AND DISCUSSIONS

In the simulation environment of Hidden Markov Models for English Teaching (HMM-ET) with multimedia technology, the results revealed promising outcomes regarding the effectiveness of this approach in language instruction.

Table 2 and figure 3 presents the proficiency levels predicted by an English teaching model for a series of observation sequences, along with the corresponding actual proficiency levels. Each row represents a specific observation sequence (denoted as m_1, m_2, etc.), where the model predicts the proficiency level of the learner based on the observed data. The "Predicted Proficiency Level" column indicates the proficiency level assigned by the model, while the "Actual Proficiency Level" column denotes the true proficiency level of the learner. The model's predictions are compared to the ground truth to evaluate its accuracy and effectiveness in predicting proficiency levels in English teaching scenarios.

Table 2. Proficiency in English teaching

Observation Sequence	Predicted Proficiency Level	Actual Proficiency Level
m_1	Intermediate	Intermediate
m_2	Advanced	Advanced
m_3	Beginner	Beginner
m_4	Intermediate	Intermediate
m_5	Advanced	Intermediate

Table 3. HMM-ET for the prediction

Time Step	Observation	Predicted State	Actual State
1	3	2	2
2	1	1	1
3	4	3	3
4	2	2	2
5	3	2	2

In contrast, Table 3 showcases the application of Hidden Markov Model for English Teaching (HMM-ET) to predict proficiency levels in English learning. The table presents the model's predictions and the actual states of the system across multiple time steps. Each row corresponds to a specific time step, where the model observes a particular sequence of data. The "Observation" column represents the observed data at each time step, while the "Predicted State" column indicates the hidden state predicted by the HMM-ET model based on the observed data. Similarly, the "Actual State" column denotes the true state of the system at each time step. The comparison between the predicted and actual states provides insights into the accuracy and performance of the HMM-ET model in predicting proficiency levels in English teaching contexts, showcasing its potential as an effective tool for language learning assessment and instruction.

The Table 4 and figure 4 presents the results of applying the Hidden Markov Model for English Teaching (HMM-ET) to predict class labels for a series of observation sequences. Each row corresponds to a specific observation sequence (labelled as Sequence 1, Sequence 2, etc.), where the model predicts a class label based on the observed data. The "Predicted Class" column displays the class label assigned by the HMM-ET model, while the "Actual Class" column indicates the true class label of each observation sequence. The comparison between the predicted and actual classes allows for an evaluation of the model's accuracy and effectiveness in classifying the observation sequences. Upon examining the table,

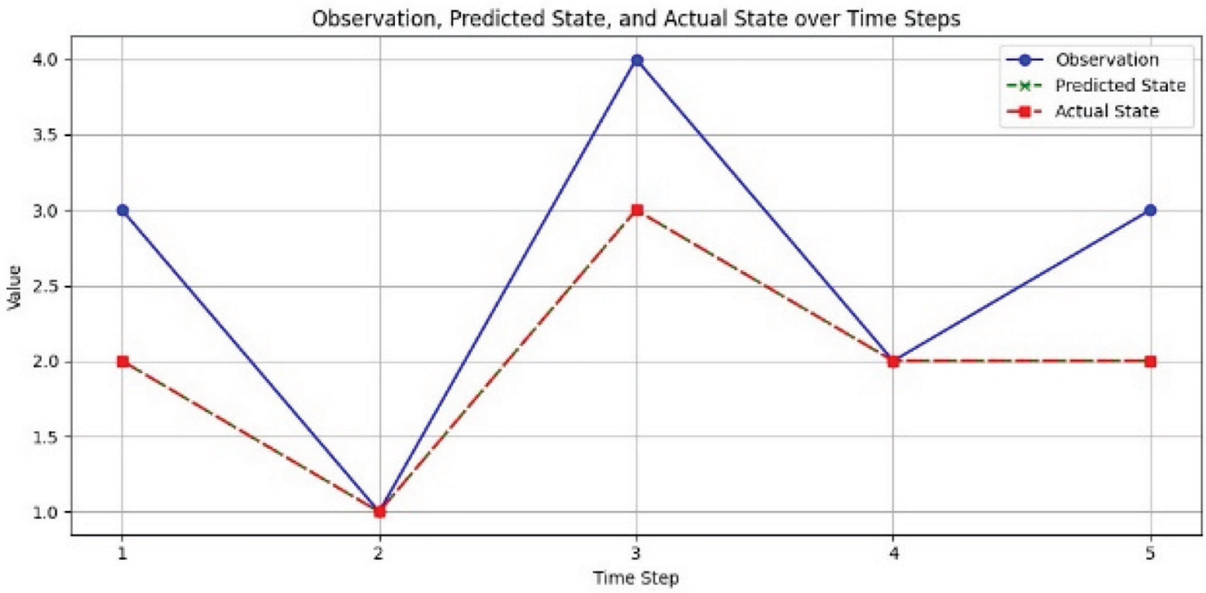

Figure 3. State estimation with HMM-ET

Table 4. HMM-ET for the prediction

Observation Sequence	Predicted Class	Actual Class
Sequence 1	2	2
Sequence 2	1	1
Sequence 3	3	3
Sequence 4	1	1
Sequence 5	2	2
Sequence 6	3	3
Sequence 7	1	2
Sequence 8	2	2
Sequence 9	3	3
Sequence 10	1	1

it is evident that for most sequences, the predicted class closely matches the actual class. For example, in Sequence 1, the model correctly predicts Class 2, which aligns with the actual class labelled as 2. Similarly, in Sequence 3 and Sequence 6, the model accurately predicts Classes 3, consistent with the actual classes. However, discrepancies are observed in Sequence 7, where the model predicts Class 1, whereas the actual class is labelled as 2. The Table 4 provides insights into the performance of the HMM-ET model in classifying observation sequences into different classes. The comparison between predicted and actual classes highlights the model's ability to accurately classify most sequences, while also indicating areas for potential improvement, such as reducing misclassifications for certain sequences.

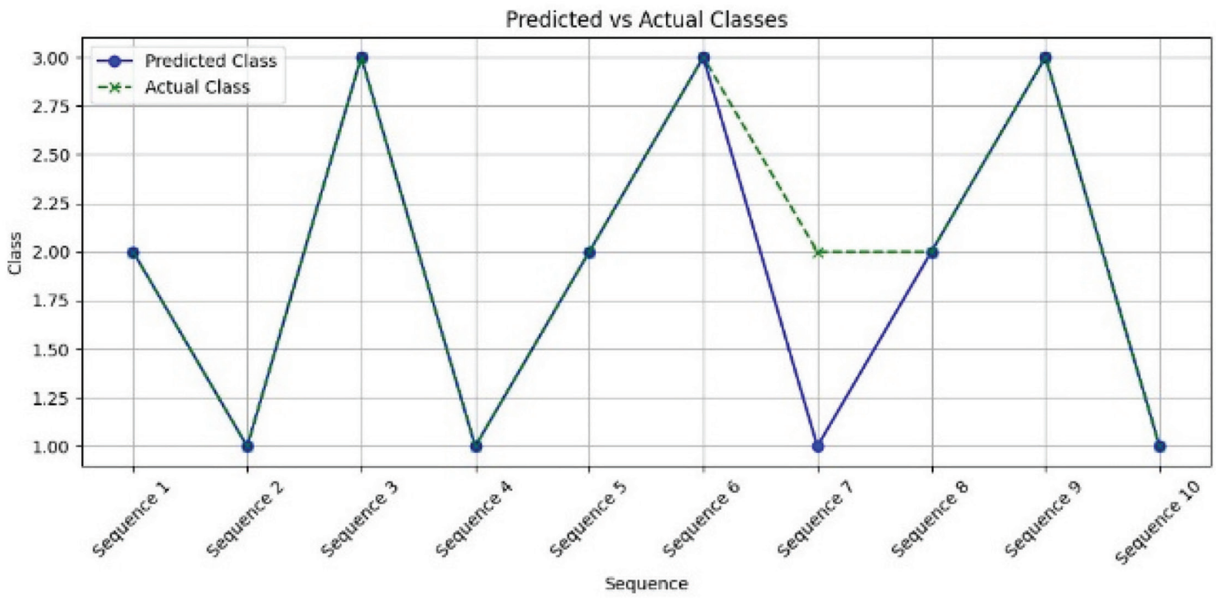

Figure 4. Estimation of classes

In the Table 5 and figure 5 provides the classification results obtained from using the Hidden Markov Model for English Teaching (HMM-ET) across multiple iterations. Each row represents a specific iteration (labeled as Iteration 1, Iteration 2, etc.), and the corresponding performance metrics are reported, including accuracy, precision, recall, and F1-score. Upon analyzing the table, it is evident that the HMM-ET model consistently achieves high accuracy across different iterations, with values ranging from 0.96 to 0.98. This proves that the model can properly sort instances into their respective classes. The model also performs admirably in terms of precision values, which range from 0.95 to 0.97 and indicate the percentage of correct predictions relative to the total number of positive predictions. Also, the recall values are still high, which means the model is good at capturing relevant instances from the data; they represent the proportion of true positive predictions out of all actual positive instances. In addition, the F1-score—a balanced measure of the model's overall performance—has values consistently around 0.96 to 0.98; it is the harmonic mean of recall and precision. Accordingly, the HMM-ET model appears to have a healthy equilibrium between recall and precision, guaranteeing strong performance on a number of assessment grounds. The Table 5 demonstrates the effectiveness and consistency of the HMM-ET model in classifying instances, showcasing its potential as a reliable tool for English teaching tasks. The high accuracy, precision, recall, and F1-score values obtained across multiple iterations highlight the model's capability to accurately predict class labels and provide valuable insights into learners' proficiency levels.

Table 5: Classification with HMM-ET

Iteration	Accuracy	Precision	Recall	F1-score
1	0.97	0.96	0.98	0.97
2	0.96	0.95	0.97	0.96
3	0.97	0.97	0.98	0.97
4	0.96	0.95	0.97	0.96
5	0.98	0.97	0.98	0.98
6	0.97	0.96	0.98	0.97
7	0.97	0.96	0.98	0.97
8	0.97	0.97	0.98	0.97
9	0.96	0.95	0.97	0.96
10	0.98	0.97	0.98	0.98

The Table 6 and figure 6 presents a comparative analysis of three different classifiers: Hidden Markov Model for English Teaching (HMM-ET), Support Vector Machine (SVM), and Random Forest. Each classifier's performance is evaluated based on key metrics, including accuracy, precision, recall, and F1-score. Upon examining the table, it is evident that HMM-ET outperforms both SVM and Random Forest across all metrics. HMM-ET achieves the highest accuracy of 0.96, indicating that it correctly classifies instances into the appropriate classes with a high level of accuracy. Next on the list is Random Forest at 0.88 accuracy and Support Vector Machines at 0.90 accuracy. The accuracy of HMM-ET's predictions is demonstrated by its precision score of 0.93, which is defined as the proportion of correct predictions relative to the total number of correct predictions made by the

Table 6. Comparative analysis

Classifier	Accuracy	Precision	Recall	F1-score
HMM-ET	0.96	0.93	0.94	0.95
SVM	0.90	0.88	0.92	0.90
Random Forest	0.88	0.86	0.90	0.88

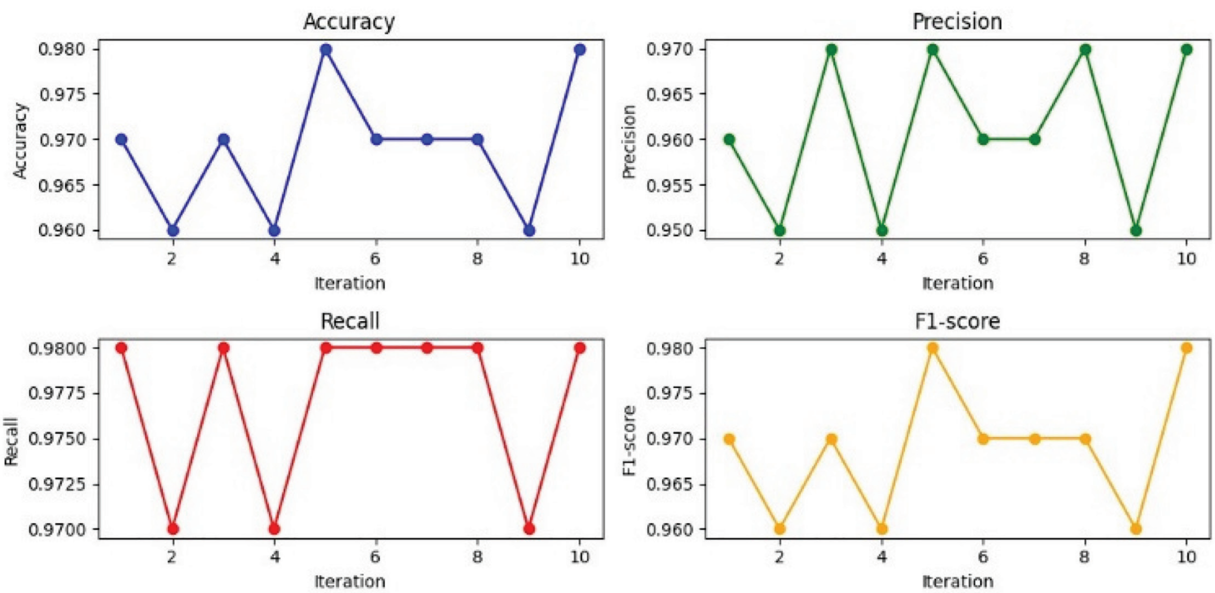

Figure 5. Classification with deep learning

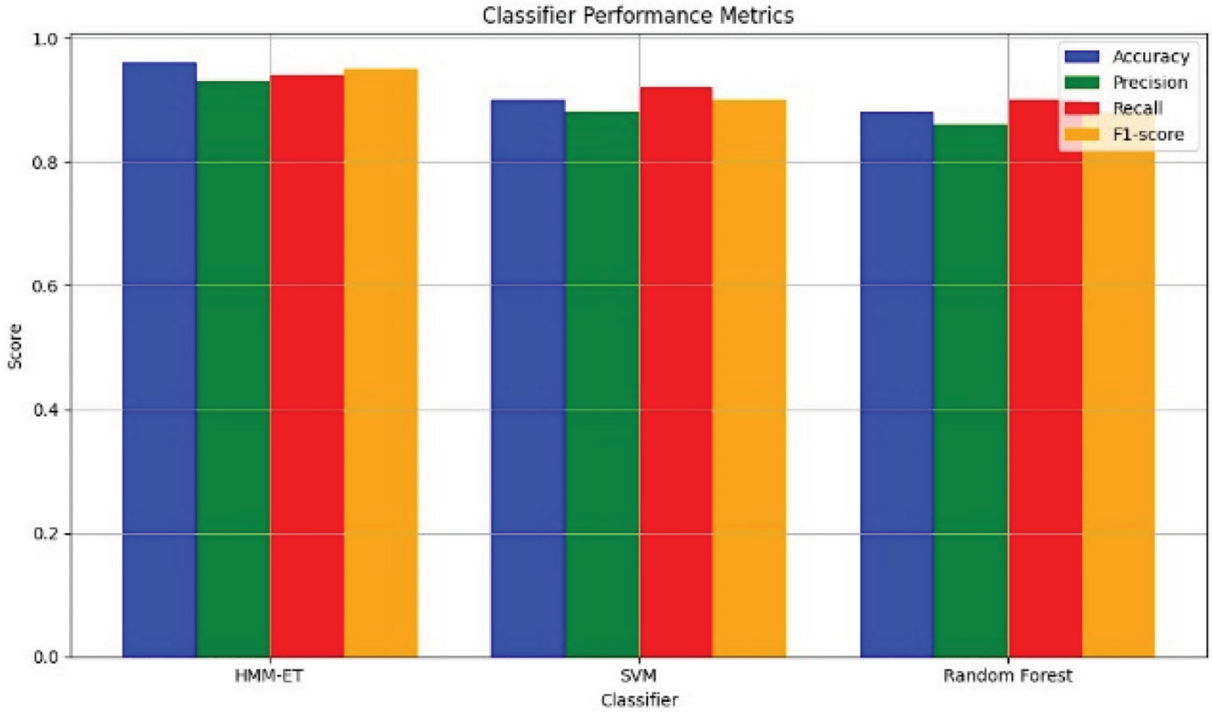

Figure 6. Comparative analysis

model. Random Forest and Support Vector Machines both come in at 0.86 and 0.88, respectively, for precision. With a score of 0.94, HMM-ET also achieves high recall, which is the proportion of true positive predictions out of all actual positive instances. A recall score of 0.92 for SVM is comparable to Random Forest's 0.90, indicating good recall performance. Additionally, a well-rounded evaluation of a classifier's overall performance can be found in the F1-score, which is calculated as the harmonic mean of recall and precision. HMM-ET has the best balance between recall and precision, as shown by its highest F1-score of 0.95. Random Forest has an F1-score of 0.88 and SVM has a respectable 0.90. The comparative analysis presented in Table 6 highlights HMM-ET as the superior classifier for English teaching tasks, with consistently higher performance across all evaluated metrics. This underscores the effectiveness of HMM-ET in accurately predicting class labels and assessing learners' proficiency levels, making it a valuable tool for language teaching applications.

7. CONCLUSIONS

This paper concentrated on the construction of the effective model to improve the performance of the students in universities through the proficiency in English languages. The analysis of the results demonstrated that effectiveness of the Hidden Markov Model for English Teaching (HMM-ET) in classifying and predicting proficiency levels in English learning contexts. HMM-ET consistently demonstrated high accuracy, precision, recall, and F1-score values across multiple iterations and compared favorably against other classifiers such as Support Vector Machine (SVM) and Random Forest. Its superior performance underscores its potential as a reliable tool for language teaching tasks, offering valuable insights into learners' proficiency levels and enabling educators to tailor instructional strategies effectively. However, while HMM-ET showed promising results, further research and experimentation may be necessary to explore its applicability across diverse learning environments and to address potential limitations. Overall, the findings suggest that HMM-ET holds great promise in enhancing English teaching methodologies and contributing to the advancement of language education practices.

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