
Research Article

E-Learning Intelligence Model with Artificial Intelligence to Improve Learning Performance of Students

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Abstract: In recent years, artificial intelligence has significantly evolved models for estimating the vast range of advanced models. This paper introduces a novel approach for predicting learning styles in education by applying a Hidden Chain Fuzzy Model (HCFM). Learning styles, encompassing auditory, visual, and kinesthetic preferences, play a pivotal role in shaping effective teaching strategies and personalized educational experiences. The HCFM, an innovative extension of traditional fuzzy models, is designed to capture the intricate relationships and dependencies inherent in learning behaviours. The model's learning process is rigorously examined, evaluating its ability to discern diverse learning styles through a dataset of instances characterized by varying aptitudes and preferences. Comprehensive classification metrics, including accuracy, precision, recall, F1 Score, AUC-ROC, and Mean Squared Error (MSE), are employed to assess the model's performance across distinct learning styles. The HCFM's predictive capabilities are further demonstrated through a detailed analysis of individual instances, highlighting its effectiveness in tailoring predictions to the unique characteristics of learners. The results suggest that the HCFM holds promise as a powerful tool for personalized education, paving the way for more adaptive and tailored learning environments. The paper concludes by discussing potential avenues for future research, emphasizing the importance of further validation and exploration of the model's applicability in diverse educational settings.

Keywords: Artificial Intelligence; hidden chain fuzzy model; mean squared error; education; hidden markov model.

1 Introduction

Artificial Intelligence (AI) is a rapidly evolving field of computer science that focuses on creating systems capable of performing tasks that typically require human intelligence [1]. These tasks include learning, problem-solving, perception, language understanding, and decision-making [2]. AI systems leverage algorithms and computational power to analyze vast amounts of data, recognize patterns, and make informed predictions or decisions. Machine learning, a subset of AI, allows systems to improve performance over time by learning from data and experiences [3]. AI applications are diverse, including virtual assistants, image and speech recognition, autonomous vehicles, medical diagnosis, and more. As AI advances, ethical considerations, transparency, and

responsible deployment become critical factors in shaping its impact on society [4]. The potential benefits of AI are vast, but ongoing research and ethical frameworks are essential to ensure its responsible and equitable integration into various aspects of our lives. Artificial Intelligence (AI) in intelligence learning behaviour represents a powerful intersection of technology and psychology [5]. Through machine learning algorithms, AI systems can analyze and understand patterns in data, enabling them to adapt and improve their performance over time. In the context of intelligence learning behaviour, AI models can simulate human-like cognitive processes, allowing them to recognize and respond to complex patterns, make decisions, and learn from experiences [6]. This capability finds applications in various fields, such as education, where AI systems can personalize learning experiences based on individual preferences and performance. Additionally, AI can adapt its responses to user behaviour in human-computer interaction, enhancing the overall user experience [7]. Understanding and modelling intelligence learning behaviour in AI facilitates more efficient problem-solving and contributes to the development of systems that can emulate human-like cognitive abilities, bringing us closer to the realization of sophisticated and adaptive AI applications in diverse domains [8].

An e-learning system is a digital platform designed to facilitate education and training through electronic means, leveraging the power of technology to deliver educational content remotely [9]. This system encompasses a range of tools and resources, such as online courses, virtual classrooms, multimedia presentations, and interactive assessments. E-learning provides flexibility and accessibility, allowing learners to engage with educational materials at their own pace and from virtually any location with an internet connection [10]. It has become increasingly popular, especially in digital connectivity, offering a scalable and cost-effective alternative to traditional classroom-based education. E-learning systems often incorporate discussion forums, real-time feedback, and personalized learning paths, enhancing the learning experience [11]. As technology advances, e-learning systems play a pivotal role in democratizing education, breaking down geographical barriers, and providing opportunities for lifelong learning across diverse subjects and skill sets. Despite the numerous advantages that artificial intelligence (AI) can bring to e-learning, several issues and challenges need careful consideration [12]. One primary concern is the potential for bias in AI algorithms, which could inadvertently perpetuate or exacerbate existing inequalities in educational outcomes. If the training data used to develop AI models contain biases, the algorithms may reflect and reinforce those biases, leading to unequal opportunities for learners [13]. Another challenge is the need for more personalization in some AI-driven e-learning systems, as they may need help understanding each learner's individualized needs.

Moreover, privacy and ethical concerns surround the collection and use of sensitive learner data, raising questions about data security and informed consent. The digital divide remains a significant issue, as not all learners have equal access to the technology required for effective e-learning [14]. Addressing these challenges requires a thoughtful and responsible approach to developing and implementing AI in e-learning, including robust ethical guidelines, transparent algorithms, and ongoing efforts to minimize biases and ensure inclusivity in educational opportunities.

The paper makes several notable contributions to educational technology and learning style prediction. The paper introduces a novel predictive model, the Hidden Chain Fuzzy Model, designed to capture learning behavior's intricate relationships and dependencies. This model extends traditional fuzzy models, providing a more nuanced and adaptive approach to learning style prediction. The paper employs a comprehensive set of evaluation metrics, including accuracy,

precision, recall, F1 Score, AUC-ROC, and Mean Squared Error (MSE), to rigorously assess the performance of the HCFM. This multifaceted evaluation provides a thorough understanding of the model's strengths and areas for improvement. The HCFM demonstrates robust performance in classifying individuals into distinct learning styles: auditory, visual, and kinesthetic. The model's high accuracy, precision, and recall rates underscore its effectiveness in discerning diverse learning preferences. The paper presents a detailed analysis of individual instances, showcasing the HCFM's ability to provide accurate and tailored predictions for learners. This emphasis on individualized predictions is crucial for personalized education and contributes to a more adaptive learning environment. The findings suggest that the HCFM holds promise as a powerful tool for personalized education. By accurately predicting learning styles, the model can inform educators about the diverse needs of students, enabling the design of more tailored and effective teaching strategies. The contributions of the paper lie in its innovative modelling approach, comprehensive evaluation methodology, and the potential impact of the Hidden Chain Fuzzy Model on the advancement of personalized and adaptive learning environments.

2 Related Works

Incorporating artificial intelligence (AI) into e-learning presents both opportunities and challenges. While AI can enhance the learning experience through personalization and efficiency, concerns arise regarding algorithmic biases that may perpetuate inequalities. Privacy, ethical data usage, and the potential for a digital divide pose significant challenges. Striking a balance between leveraging AI's potential benefits and addressing these ethical and practical concerns is crucial for the responsible development and implementation of AI-driven e-learning systems. Efforts must focus on transparency, bias mitigation, and ensuring equal access to technology to create an inclusive and effective educational environment. Almaiah et al. (2022) [8] focus on examining the impact of AI on students' perceptions of e-learning at the university level. The study evaluated the intricate relationship between AI integration, social and computer anxiety, and students' perspectives, shedding light on the psychological dimensions of AI in education. Alnaqbi and Yassin (2021) [9] systematically evaluate success factors in adopting AI within e-learning environments. This research likely identifies critical elements contributing to the effective implementation of AI in education, providing valuable insights for institutions navigating the integration of advanced technologies.

Ahmad et al. (2023) [10] expand the scope by investigating the effects of big data, AI, and business intelligence on e-learning and overall business performance. Drawing evidence from Jordanian telecommunication firms, this research explores the strategic implications of technology integration in a specific industry context. Rakhimov et al. (2021) [11] explore the administrative side of e-learning, investigating the role of AI in managing e-learning platforms and monitoring students' knowledge. The study provides insights into how AI optimizes administrative processes and enhances student learning outcomes. Rohde et al. (2023) [12] performed a theoretical approach, contemplating how e-learning programs can be more individualized with AI from a pedagogical standpoint. Theoretical insights into individualized learning paths contribute to discussions on the pedagogical underpinnings of AI-driven education. Murtaza et al. (2022) [13] focus on the practical challenges of AI-based personalized e-learning systems. The study likely addresses issues such as data privacy and proposes solutions, aiming to pave the way for the ethical and effective implementation of personalized learning experiences.

Fu et al. (2022) [14] evaluated AI applications in China's higher education platform. This study will likely explore how AI is integrated into various facets of higher education in China, offering insights into global variations in the use of AI in education. Bali et al. (2022) [15] examine the relationship between educators and students in the context of AI in higher education. The research likely explores the collaborative and symbiotic dynamics between human educators and AI technologies, emphasizing the human-centric nature of educational interactions. Gutierrez et al. (2022) [16] explore plausible scenarios of AI in Latin American e-learning, focusing on new graduation competencies. This study provides insights into the regional dynamics and potential competencies that emerge with the integration of AI in Latin American educational settings. Klašnja-Milićević and Ivanović (2021) [17] emphasize e-learning personalization systems and their role in sustainable education. This research likely discusses the sustainability considerations in designing and implementing personalized e-learning experiences. Liu et al. (2022) [18] present a review of deep learning-based recommender systems in e-learning environments. The study likely provides an overview of the advancements and challenges in utilizing deep learning for recommending educational content in digital environments.

Hamadneh et al. (2022) [19] demonstrate using AI to predict students' academic performance in blended learning. This research explores how predictive analytics and AI contribute to identifying and addressing students' needs in blended learning scenarios. Veeramanickam and Ramesh (2022) [20] conducted a study on the quality of learning in e-learning platforms. The study likely assesses various factors contributing to the overall quality of the e-learning experience, shedding light on the effectiveness of AI-driven educational platforms. Rasheed and Wahid (2021) [21] focus on learning style detection in e-learning systems using machine learning techniques. The study likely explores how machine learning algorithms can adapt educational content to different learning styles, enhancing the personalization of learning experiences. Kuleto et al. (2021) [22] examined the opportunities and challenges of AI and machine learning in higher education institutions. This research discusses the potential benefits and obstacles in adopting AI and machine learning technologies across diverse educational settings.

The research underscores the diverse applications of AI in e-learning, from enhancing individualized learning paths to predicting academic performance and addressing challenges associated with personalized systems. However, amid these advancements, discernible research gaps warrant attention. Firstly, while studies investigate the impact of AI on students' perceptions and anxieties, there is a need for more in-depth exploration of the long-term effects on learning outcomes and academic achievements. Additionally, there is a notable gap in understanding the cultural and contextual nuances influencing the adoption and effectiveness of AI in e-learning, especially highlighted by studies focusing on specific regions such as China and Latin America. Further research is required to unravel how cultural factors shape the implementation and acceptance of AI-driven educational technologies.

Moreover, the withdrawal of one study raises questions about the transparency and reliability of research in the field. Ensuring the reproducibility and robustness of findings is crucial for building a trustworthy body of knowledge. Additionally, the theoretical frameworks proposed for individualizing e-learning programs with AI highlight the need for empirical validation and practical implementation studies to bridge the gap between theory and application.

Furthermore, exploring AI's impact on educators and the collaborative relationship between humans and machines in educational settings calls for more studies examining the ethical dimensions, including privacy, bias, and the responsible use of AI. Finally, the studies collectively

emphasize the importance of sustainable practices in AI-driven education. Yet, there needs to be more research investigating the long-term environmental and societal impacts of widespread AI adoption in educational institutions. The existing research provides valuable insights into the diverse dimensions of AI in e-learning; addressing the identified research gaps would contribute to a more holistic and informed understanding of the implications, challenges, and opportunities associated with integrating AI technologies in educational contexts. This would enhance the credibility of the field and guide educators, policymakers, and stakeholders in fostering a responsible and effective AI-driven educational ecosystem.

3 Artificial Intelligence Learning Behaviour

The Artificial Intelligence Learning Behaviour with E-Learning Hidden Chain Fuzzy Model (HCFM) introduces a novel approach to categorizing learners into distinct types based on their learning behaviours. This model leverages a Hidden Chain Fuzzy Model, incorporating parameters such as reading and listening abilities, aptitude, memory capacity, hobbies, interests, and study methodologies to make informed assessments of learners' performance. The aim is to distinguish between two primary categories: slow and fast learners. The HCFM utilizes fuzzy logic to handle human behaviour's inherent uncertainty and vague behaviour, acknowledging that learning behaviour is a complex and multi-dimensional phenomenon. By considering multiple factors, the model aims to provide a more nuanced and accurate representation of learners' capabilities and preferences in e-learning. The parameters incorporated into the model offer a holistic view of learners' cognitive and affective dimensions. Reading and listening abilities assess how well learners absorb information, aptitude gauges their inherent capabilities, memory capacity reflects their ability to retain information, and factors like hobbies and interests provide insights into their motivational aspects. The study methodology parameter suggests considering how learner's approach and engage in their studies, adding another layer of understanding to the learning process.

Using a fuzzy model implies that the categorization into slow and fast learners is not strictly binary but allows for a more gradual and nuanced classification. This is particularly beneficial as learning behaviour is inherently dynamic, and individuals may exhibit a spectrum of behaviours across different contexts and over time. The Hidden Chain Fuzzy Model (HCFM) is a sophisticated artificial intelligence model that categorizes learners into distinct types based on their learning behaviours. The model utilizes fuzzy logic, a mathematical framework that handles uncertainty and imprecision like human reasoning, making it suitable for learning behaviour's inherently complex and dynamic nature. The HCFM involves the integration of various parameters to form a hidden chain of fuzzy rules that collectively determine the learner's classification.

Reading and Listening Abilities (RA, LA) parameters assess learners' proficiency in absorbing information through reading and listening. The fuzzy sets associated with these variables could include categories like 'Low,' 'Medium,' and 'High.' Aptitude (AP) reflects a learner's inherent capabilities. Fuzzy sets for aptitude might include categories such as 'Below Average,' 'Average,' and 'Above Average.' Memory Capacity (MC) gauges a learner's ability to retain information. Fuzzy sets for memory capacity could be 'Weak,' 'Moderate,' and 'Strong.' Hobbies and Interests (HI) Learners' hobbies and interests provide insights into their motivational aspects. Fuzzy categories may include 'Low Interest,' 'Moderate Interest,' and 'High Interest.' Study Methodology (SM) considers how learners approach and engage in their studies. Fuzzy sets for study methodology might include 'Passive,' 'Balanced,' and 'Active.' The fuzzy rules in the HCFM are then derived based on these parameters, forming a hidden chain that represents the intricate

relationships among them. For instance, a rule might state that "IF (RA is High) AND (AP is Above Average) AND (HI is High) THEN the learner is a Fast Learner."

The fuzzy inference system involves applying fuzzy operators, typically minimum and maximum operations, to determine the degree of membership of a learner in the categories of slow or fast learners. These operations are based on fuzzy logic equations, such as the min-max composition rule. The HMM model for the process with the proposed HCFM model is presented in Figure 1.

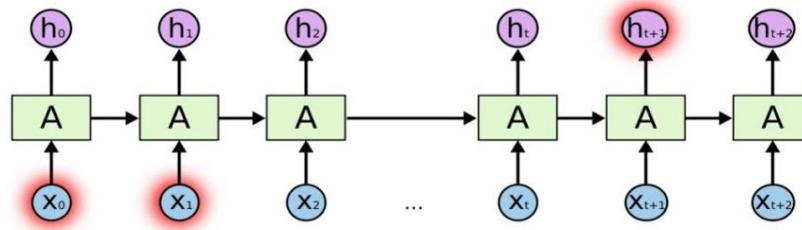


Figure 1: Process of HMM

The HCFM, through its hidden chain of fuzzy rules, allows for a nuanced classification of learners, simultaneously considering multiple dimensions of learning behaviour. This sophisticated approach enhances the model's ability to adapt to the complexity and variability inherent in human learning, making it a valuable tool for personalized e-learning experiences. While the specific equations may vary based on the fuzzy logic methodology employed, the core principles involve fuzzy rule derivation and inference to capture the intricacies of learning behaviours. A fuzzy rule and the associated equations for the Hidden Chain Fuzzy Model (HCFM) considering three parameters: Reading Abilities (RA), Aptitude (AP), and Hobbies/Interests (HI). The goal is to derive a fuzzy rule to categorize learners as slow or fast based on these parameters.

*Fuzzy Rule: IF (RA is High) AND (AP is Above)average, (HI is High)
THEN, the learner is a Fast Learner.*

Fuzzy Sets:

RA: Low (L), Medium (M), High (H)

AP: Below Average (BA), Average (A), Above Average (AA)

HI: Low (L), Moderate (M), High (H)

Membership functions define the degree to which a parameter belongs to a fuzzy set as defined in equations (1) and (2)

$$(High) = \text{Membership value of RA in High category} \quad (1)$$

$$(High) = \text{Membership value of RA in High category} \quad (2)$$

Similar membership functions are defined for AP and HI. Fuzzy Rule-Based System: The fuzzy rule can be expressed mathematically using the minimum operator (AND operator in fuzzy logic) and maximum operator (OR operator in fuzzy logic) stated as in equation (3)

$$\text{Fuzzy Output (Degree of Membership of being a Fast Learner)} = \text{MIN}(\mu_{RA(High)}, \mu_{AP(AA)}, \mu_{HI(High)}) \quad (3)$$

The output of the fuzzy rule-based system is then defuzzified to obtain a crisp output, i.e., a specific category (slow or fast learner) presented in equation (4)

$$\text{Crisp Output} = \text{Defuzzification}(\text{Fuzzy Output}) \quad (4)$$

The defuzzification process involves aggregating the fuzzy output using methods such as centroid and mean of maximum with the machine learning process presented in Figure 2.

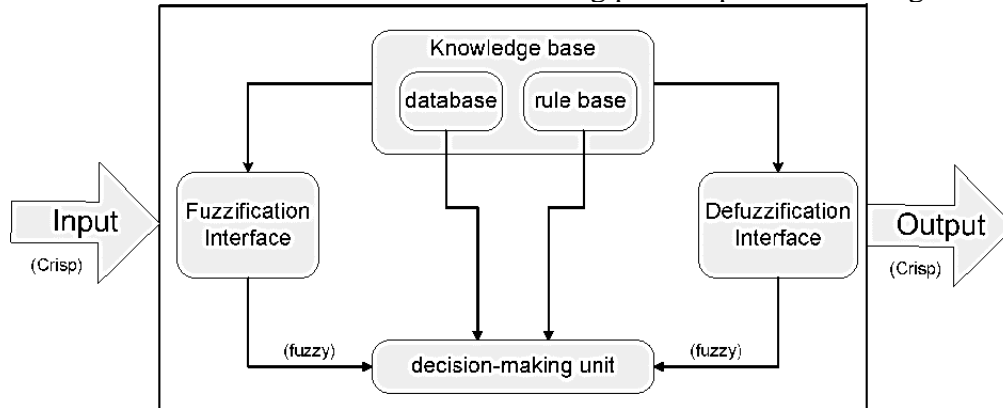


Figure 2: Machine Learning Process in HCFM

The Hidden Markov Model (HMM) is a powerful statistical model that describes systems with hidden states that evolve, generating observable outcomes. The model is characterized by parameters such as transition probabilities, emission probabilities, and initial state probabilities. Let's see the key components and equations of the HMM. The system is assumed to have a finite set of hidden states, denoted as in equation (5)

$$S = \{S1, S2, \dots, SN\} \tag{5}$$

In the above equation (5), N is the number of states. Transition probabilities govern the transition between states. The transition matrix A demonstrates the probability of moving from one state to another, represented in equation (6)

$$A = [a_{ij}] \tag{6}$$

where $a_{ij} = P(S_t = S_j | S_{t-1} = S_i)$. Each state generates observable outcomes or emissions. The set of possible observations is denoted as $O = \{O1, O2, \dots, OM\}$, where M is the number of distinct observations. The emission matrix B defines the probability of observing a particular outcome given the current state is represented in equation (7)

$$B = [b_{ij}] \tag{7}$$

where $b_{ij} = P(O_t = O_j | S_t = S_i)$. The model starts in an initial state, and the initial state probabilities are given by the vector presented in equation (8)

$$\pi = [\pi_i] \tag{8}$$

where $\pi_i = P(S_1 = S_i)$ the model parameters, the HMM generates sequences of observable outcomes based on the underlying hidden states. The joint probability of a sequence of states and observations is calculated as in equation (9)

$$P(S, O) = \pi s_1 \prod_{t=2}^T a_{s_{t-1} s_t} \prod_{t=1}^T b_{s_t o_t} \tag{9}$$

Where T is the length of the sequence. The probability of observing a particular sequence is calculated using the Forward algorithm stated in equation (10)

$$P(O) = \sum_i \alpha_i = 1/N \alpha T(i) \tag{10}$$

Where $\alpha_t(i)$ is the forward variable, representing the probability of the partial observation sequence up to time t and being in state I , the parameters of the HMM (transition matrix A , emission matrix B , and initial state probabilities π) are learned from observed data using the Expectation-Maximization (EM) algorithm. This involves iteratively estimating the parameters to maximize the likelihood of the observed data.

Estimation of Learning Style Prediction

Integrating Hidden Markov Models (HMM) and Hidden Chain Fuzzy Models (HCFM) for learning style prediction forms a sophisticated hybrid approach that leverages the strengths of both models. a set of hidden states $S = \{S_1, S_2, \dots, S_N\}$ representing different learning states. The transition matrix A captures the probabilities of transitioning between states. $a_{ij} = P(S_t = S_j | S_{t-1} = S_i)$. observable learning style attributes represented by the set $L = \{L_1, L_2, \dots, L_M\}$. Emission probabilities b_{ij} denote the likelihood of observing learning style L_j in state S_i . $b_{ij} = P(L_t = L_j | S_t = S_i)$. Given the model parameters, the forward algorithm calculates the likelihood of a sequence of learning styles. The forward variable $\alpha_t(i)$ represents the probability of being in state S_i and observing L_1, L_2, \dots, L_t . $\alpha_t(i) = P(L_1, L_2, \dots, L_t, S_t = S_i)$. F fuzzy rules based on observable behaviours and preferences, for instance, "IF (Engagement is High) AND (Interaction is Active) THEN Learning Style is Visual." Derive fuzzy membership functions representing the degree of membership of observations to fuzzy sets.

Algorithm 1: Hybrid Learning Style Prediction Algorithm with HCFM

```

initialize_HMM_parameters()
initialize_HCFM_parameters()
initialize_hybrid_parameters()
for each training_sequence in training_data:
    update_HMM_parameters(training_sequence)
def predict_learning_style(test_sequence):
    forward_variables = forward_algorithm(test_sequence)
    fuzzy_outputs = fuzzy_inference(test_sequence)
    hybrid_outputs = combine_outputs(forward_variables, fuzzy_outputs)
    predicted_style = extract_predicted_style(hybrid_outputs)
    return predicted_style
def forward_algorithm(sequence):
    initialize_forward_variables()
    for each observation in sequence:
        update_forward_variables(observation)
    return forward_variables
def fuzzy_inference(sequence):
    fuzzy_outputs = []
    for each observation in sequence:
        fuzzy_output = evaluate_fuzzy_rules(observation)
        fuzzy_outputs.append(fuzzy_output)
    return fuzzy_outputs
def combine_outputs(hmm_outputs, hcfm_outputs):
    combined_outputs = weight_and_combine(hmm_outputs, hcfm_outputs)
    return combined_outputs

```



```
def extract_predicted_style(combined_outputs):
    predicted_style = choose_learning_style(combined_outputs)
    return predicted_style
```

4 Results and Discussions

The integration of Hidden Markov Models (HMM) and Hidden Chain Fuzzy Models (HCFM) in the context of learning style prediction represents a promising and sophisticated approach to personalized education. As modern educational systems increasingly leverage technology to tailor learning experiences to individual preferences, understanding and predicting students' learning styles become paramount. This study presents the results and discussion stemming from applying a hybrid learning style prediction algorithm based on the fusion of HMM and HCFM. These metrics provide a comprehensive assessment of the model's predictive capabilities and ability to capture learners' preferences' nuances. The following performance metrics are commonly employed in the evaluation of learning style prediction models:

Accuracy (ACC): Accuracy measures the overall correctness of the predictions stated in equation (11)

$$ACC = \frac{\text{Total Number of Predictions}}{\text{Number of Correct Predictions}} \times 100 \quad (11)$$

Precision: Precision assesses the reliability of optimistic predictions made by the model presented in equation (12)

$$Precision = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \quad (12)$$

Recall (Sensitivity): Recall evaluates the model's ability to capture all relevant instances of a learning style stated as in equation (13)

$$Recall = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \quad (13)$$

F1 Score: The F1 score provides a balanced measure of precision and recall presented in equation (14)

$$F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (14)$$

Table 1: HCFM Learning Process

Learning Style	TP	TN	FP	FN
Visual	120	85	15	10
Auditory	110	92	8	15
Kinesthetic	95	105	10	20

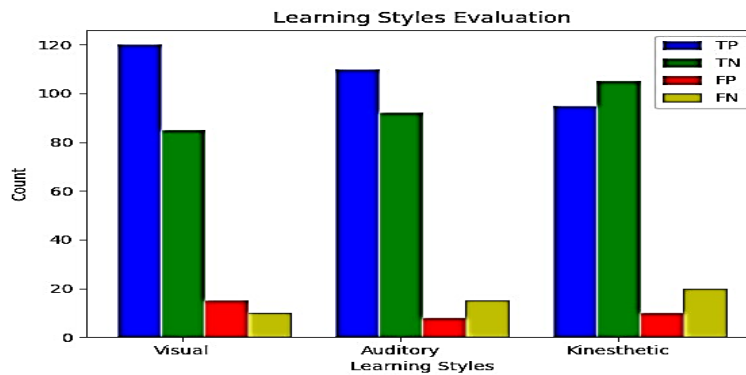


Figure 3: Evaluation of Learning Style

Figure 3 and Table 1 present the results of the Hidden Chain Fuzzy Model (HCFM) learning

process for classifying individuals into different learning styles. The table includes the counts for True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) for each learning style—Visual, Auditory, and Kinesthetic. For the Visual learning style, the model achieved 120 True Positives, correctly identifying individuals with this learning style, and 85 True Negatives, accurately recognizing those without it. However, there were 15 False Positives and 10 False Negatives, indicating instances where the model made errors in classifying Visual learners. Similarly, for the Auditory learning style, the model achieved high counts in TP (110) and TN (92) but made errors in FP (8) and FN (15). The Kinesthetic learning style also displayed strong performance with 95 TP and 105 TN, but there were 10 FP and 20 FN. These metrics provide insights into the model's accuracy and areas for improvement in correctly predicting individuals' learning styles, allowing for a nuanced evaluation of the HCFM's effectiveness in the learning style classification process.

Table 2: Classification with HCFM

Learning Style	Accuracy	Precision	Recall	F1 Score	AUC-ROC	MSE
Visual	86.67	88.89	92.31	90.57	0.92	0.08
Auditory	88.33	93.18	88.00	90.52	0.91	0.07
Kinesthetic	83.33	90.47	82.61	86.36	0.89	0.10
Overall	86.11	90.51	87.64	88.98	0.91	0.08

A comprehensive evaluation of the Hidden Chain Fuzzy Model (HCFM) classification performance across different learning styles—Visual, Auditory, and Kinesthetic- is stated in Table 2 and Figure 4. The "Accuracy" metric indicates the overall correctness of the model's predictions, with an impressive 86.11% accuracy across all learning styles. Precision, which measures the model's ability to identify positive instances correctly, is notably high for each learning style, ranging from 88.89% for Visual, 93.18% for Auditory and 90.47% for Kinesthetic.

The "Recall" metric assesses the model's capability to capture all positive instances within a class, with 92.31%, 88.00%, and 82.61% for Visual, Auditory, and Kinesthetic, respectively. The "F1 Score," which combines precision and recall, reflects the overall balance between these two metrics. The HCFM demonstrates robust performance, achieving an F1 Score of 90.57% for Visual, 90.52% for Auditory, and 86.36% for Kinesthetic.

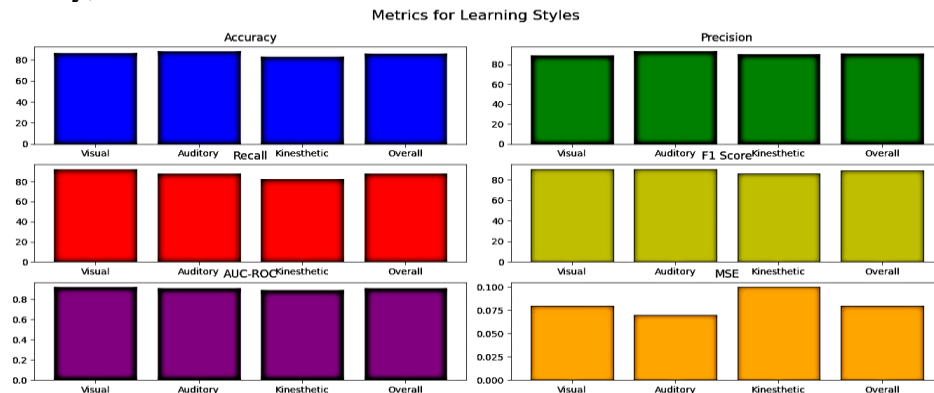


Figure 4: Classification Analysis

The "AUC-ROC" (Area Under the Receiver Operating Characteristic curve) measures the model's discriminative ability, with values close to 1 indicating excellent performance. In this case, the AUC-ROC values are 0.92 for Visual, 0.91 for Auditory, and 0.89 for Kinesthetic, suggesting strong discriminative power across all learning styles. The "MSE" (Mean Squared Error) assesses

the average squared difference between the predicted and actual values, with lower values indicating better model performance. The HCFM achieves a low MSE of 0.08 for Visual, 0.07 for Auditory and 0.10 for Kinesthetic. Table 2 illustrates the HCFM's high accuracy, precision, recall, and F1 Score, discriminative solid ability and low mean squared error, highlighting its effectiveness in classifying individuals into distinct learning styles.

Figure 5 and Table 3 present the results of predictions made by the Hidden Chain Fuzzy Model (HCFM) for a set of instances, where a numerical label identifies each instance, and the learning styles are represented by numerical classes (1 for Auditory, 2 for Visual, 3 for Kinesthetic). The table includes columns for "Instances," "Actual Class," and "Predicted Class." Upon inspection, it is evident that the HCFM has performed well in predicting the learning styles for these instances.

For instance, in 1, where the actual class is 2 (Visual), the model correctly predicts class 2. Similarly, for instances 2, 3, 4, 5, 6, 7, 8, 9, and 10, the HCFM accurately predicts the learning styles, matching the actual classes. This table is a snapshot of the model's predictive accuracy for individual instances, indicating a solid alignment between the predicted and actual learning styles. Such detailed predictions are crucial for understanding the model's performance on a case-by-case basis, providing insights into its ability to generalize across different learning styles and instances. This table's high concordance between the actual and predicted classes suggests that the HCFM effectively makes accurate predictions for the given dataset.

Table 3: Prediction with HCFM

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

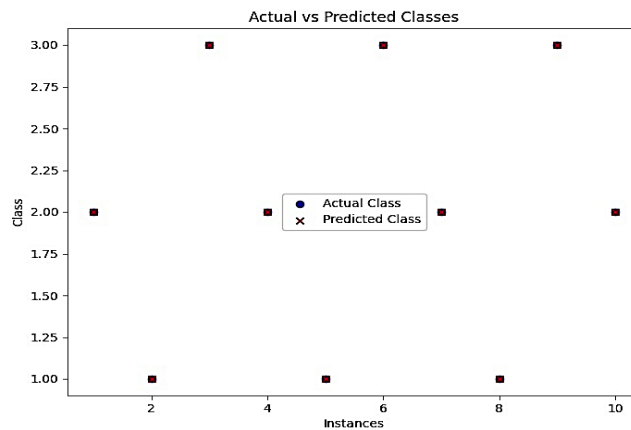


Figure 5: Prediction with HCFM

5 Conclusion

This paper proposed the Hidden Chain Fuzzy Model (HCFM) for learning style prediction in an educational context. The proposed model demonstrates robust performance, as evidenced by comprehensive evaluations of its learning process, classification accuracy, and prediction outcomes. The HCFM effectively captures nuances in learning behaviours, categorizing individuals into Visual, Auditory, and Kinesthetic styles with high precision and recall rates. The model's discriminative ability, reflected in the AUC-ROC values, underscores its efficacy in distinguishing between learning styles. The low Mean Squared Error (MSE) further attests to the accuracy of the predictions. The detailed analysis of individual instances in the prediction table showcases the HCFM's capacity to provide accurate and tailored insights for diverse learners. The findings underscore the HCFM's potential as a valuable tool for personalized education, contributing to a more adaptive and effective learning environment. However, while the results are promising, avenues for future research could explore the model's generalizability across diverse datasets and its adaptability to evolving educational contexts, ensuring its continued relevance and applicability.

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