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AI-Powered Personalized Learning Platform

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***Abstract*—This paper presents the design and evaluation of a self-learning, AI-driven chatbot developed to extract and deliver contextually relevant answers from user-uploaded articles. Implemented using Python and natural language processing (NLP) techniques, the chatbot utilizes tokenization, normalization, and cosine similarity to identify and retrieve the most relevant information from the provided text. Beyond answering user queries, the system incorporates sentiment analysis with Support Vector Machines (SVM) to assess content tone. The NLP-based chatbot achieved 90.00% accuracy, 90.84% precision, 89.41% recall, and a 0.9012 F1-Score, reflecting robust and balanced performance. In contrast, the sentiment analysis module demonstrated high precision (91.49%) but lower recall (80.37%), resulting in an F1-score of 85.57% and accuracy of 85.50%. The chatbot further enhances user experience by supplying related image links to facilitate additional learning. These results demonstrate the effectiveness of integrating NLP and machine learning for intelligent, article-driven question answering and personalized content exploration. Unlike conventional AI-based learning chatbots that depend on large pre-trained knowledge bases, the proposed system operates solely on user-uploaded articles, ensuring context-bounded and interpretable responses. The primary contribution of this work is a lightweight NLP-driven architecture that combines similarity-based question answering with sentiment-aware content analysis, enabling reliable and personalized learning without reliance on computationally intensive language models. This approach is particularly suitable for educational environments that require transparency, efficiency, and controlled knowledge sources.**

I. Introduction

In today's changing education system, Artificial Intelligence (AI) is significantly transforming how knowledge is shared and learned. Moving beyond generic teaching methods, AI-powered systems tailor educational experiences to each student's strengths, challenges, and preferences using machine learning. These platforms adjust content difficulty and presentation style based on individual progress and understanding, providing immediate feedback to identify knowledge gaps and promote effective learning. By presenting content in interactive formats aligned with students' interests, they boost motivation and strengthen engagement with the material. AI also analyzes student performance data to identify learning patterns and generate insights, helping teachers make informed decisions. This personalized approach accommodates various learning styles and speeds, enabling students to understand concepts thoroughly. For teachers, AI reduces the time spent on manual data assessment, allowing more focus on mentoring and student interaction. As technology advances, such systems support independent learning and foster ongoing skill development. They also help close educational gaps by offering quality learning experiences in remote and underserved areas, promoting equity and removing geographical barriers.

II. Related Work

Jathushan et al. [1] developed a web-based platform for Grade 10 ICT education to promote autonomous learning. The free application helps students develop and evaluate ICT skills, improving conceptual understanding and academic performance. It features an interactive homepage where students submit questions answered and ranked by users through voting, with real-time warnings for irrelevant queries. A chatbot further supports users by recommending websites and enabling quick navigation.

Sun et al. [2] proposed an intelligent online English learning platform using deep learning to enhance language skills through personalized instruction. Their system combines decision trees with neural networks to create a robust assessment framework. By analyzing large datasets, it identifies patterns that help educators refine teaching strategies. Testing shows the platform improves learning efficiency and delivers content suited to individual learner needs.

Zhou et al. [3] designed an AI-based self-learning platform to improve college students' English listening skills. Built on service, technology, and data layers, it provides real-time support, personalized materials, and performance tracking. The architecture encourages independent learning and improves daily study efficiency.

Mahroof et al. [4] introduced Edubot, an AI-supported interactive classroom system for Ordinary Level Chemistry. It offers tutorials, detailed responses, and a self-assessment module simulating exams. With over 70% component accuracy, the system effectively supplements Chemistry learning and enhances student engagement.

Diwan et al. [5] presented an automated system for generating educational dialogue components, including concise summaries and reflective quizzes. The system synthesizes content from diverse educational sources using a multi-stage pipeline that integrates semantic modeling with a natural language generation module based on GPT-2. This architecture enables dynamic, learner-adaptive educational narratives that identify when students should review fundamentals or advance, thereby improving engagement and supporting personalized learning.

Similarly, Cui et al. [6] empirically evaluated the Yixue Squirrel AI adaptive learning platform for middle school English and mathematics. Through comparative analysis against traditional instruction and the BOXFiSH system, results showed Yixue users consistently achieved superior performance. The findings highlight the effectiveness of data-driven personalized learning in improving academic outcomes.

Li et al. [7] proposed a flipped classroom model that integrates face-to-face teaching with AI-enabled online learning. Their hybrid framework combines direct instructor feedback with personalized digital tools offering adaptive assessments and tailored content. The study reports improved learner motivation, understanding, and self-regulation, emphasizing the importance of technology-integrated pedagogy.

Zhang et al. [8] developed the AISSE framework to enhance engagement and academic success in higher education using AI technologies such as intelligent tutoring systems and chatbots. The framework establishes an interactive feedback ecosystem that monitors progress and supports personalized guidance. Experimental results showed improved student–teacher interaction, higher participation, and more accurate performance evaluation.

Saqr et al. [9] conducted a cross-sectional study on AI-integrated educational technologies and their influence on Saudi university students' perceptions of e-learning. Focusing on factors like perceived usefulness and ease of use within platforms such as Moodle and Coursera, and applying the Technology Acceptance Model, the study found that self-efficacy, learning readiness, and innovativeness significantly affect adoption and continued engagement.

Cao et al. [10] examined AI-powered smart learning environments, outlining key components including intelligent tutoring, real-time analytics, adaptive delivery, and interactive interfaces. Their case studies emphasized requirements such as scalability, robustness, and user-centered design. They also highlighted multimedia integration as a critical strategy for creating immersive, multisensory language learning environments that enhance engagement, motivation, autonomy, and linguistic competence.

Building on this, recent studies advocate targeted multimedia strategies in English learning, including interactive vocabulary tasks, pronunciation modules, and multimedia storytelling. Evidence shows such multimodal approaches improve vocabulary retention, proficiency, and communicative confidence, particularly in remote or low-interaction settings.

Houda Oubalahcen et al. [11] emphasized the growing impact of AI and machine learning across sectors, including education. The COVID-19-driven shift to online learning accelerated adoption of AI-powered platforms capable of adaptive assessment and personalized tutoring. However, challenges remain, such as limited interactivity, technological barriers, time constraints, and mismatches with diverse learning styles.

To overcome these issues, modern EdTech increasingly uses intelligent recommender systems to model learner preferences and construct personalized learning paths. These AI-driven systems dynamically adapt content and recommend resources, improving engagement and outcomes while raising concerns regarding privacy, bias, and transparency.

Hazrina Hamid et al. [12] investigated AI integration within process-driven problem-based learning in pharmacy education. Using ChatGPT (GPT-3.5), their qualitative study found that conversational AI provides scaffolded support, immediate feedback, and personalized guidance, strengthening active learning and critical thinking.

Sarah A. Chauncey et al. [13] examined ethical integration of AI chatbots such as ChatGPT-4 in education. They proposed a conceptual framework emphasizing transparency, fairness, and responsible deployment. Through use cases in mathematics, English, and academic support, the study highlighted AI's potential to enhance higher-order thinking, creativity, and self-regulation while maintaining pedagogical integrity.

Finally, Sang Joon Lee et al. [14] conducted a systematic review of AI education in K–12 settings. Analysis of 25 studies (2018–2023) showed curricula commonly cover machine learning, neural networks, and AI ethics, often delivered through project-based learning. At the K–12 [15] level, they also proposed an AI model to identify learning styles (visual, auditory, reading/writing, kinesthetic) using behavioral indicators such as attention, cognitive load, and facial expressions. Among tested algorithms, the random forest achieved the highest accuracy (87.5%), confirming the model's reliability for enabling personalized instructional strategies and advancing learner-centric EdTech environments.

III. Proposed Methodology

The proposed system aims to develop an intelligent chatbot capable of answering queries related to a user-uploaded article. It employs a structured pipeline that processes input text, conducts sentiment analysis, and trains a model for effective user response. The methodology includes six key stages, illustrated in the system architecture in Fig. 1, and described below.

A. Uploading the Article

The process begins with the user uploading an article in plain text, which serves as the chatbot's knowledge base. The system then validates the input format and prepares it for further processing. Ensuring the uploaded content's accuracy and completeness is essential, as downstream tasks depend entirely on this initial input.

B. Tokenization of Text

After uploading, the raw text is tokenized by dividing it into linguistic units like words or sentences. Tokenization is essential in Natural Language Processing (NLP), transforming unstructured text into a structured format for analysis. Tools such as NLTK, spaCy, or HuggingFace Tokenizers facilitate effective tokenization. This process allows systems to interpret the grammatical and syntactic structure of the text.

C. Text Normalization

After tokenization, the text undergoes normalization to ensure consistency. This involves converting characters to lowercase, removing punctuation, stopwords, special characters, and optionally applying stemming or lemmatization. Normalization reduces noise and ensures that semantically similar words are treated uniformly, thereby improving sentiment analysis and model training performance.

D. Sentiment Analysis

The normalized text undergoes sentiment analysis to identify its emotional tone and polarity. This step reveals whether the content is positive, negative, or neutral, aiding in response customization or filtering sensitive content. Techniques like VADER, TextBlob, or transformer-based classifiers (e.g., BERT) may be used. The resulting sentiment data serves as an auxiliary signal to enhance the accuracy of subsequent responses.

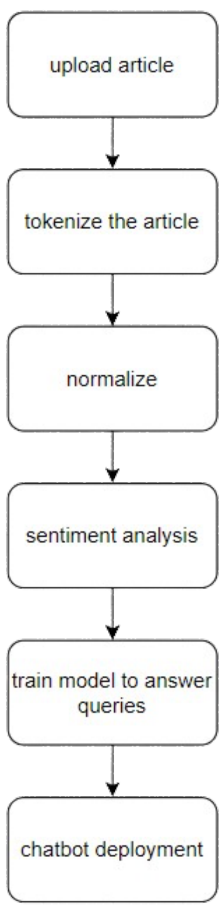

Fig. 1. Depicting project flow and architecture

E. Training the NLP Model for Question Answering

Using processed, sentiment-labeled text, an NLP model is trained to respond to user queries based on the article's content. This involves selecting an architecture such as a transformer-based model (e.g., BERT, RoBERTa, or DistilBERT) and fine-tuning it to understand the text's context. The objective is for the system to extract and generate accurate, relevant answers, considering both factual content and emotional tone.

F. Chatbot Deployment

Finally, the trained model is deployed in a production environment as an interactive chatbot. Using a user-friendly interface, users can ask questions about the uploaded article, and the system returns contextually relevant answers. The architecture ensures real-time performance, continuous learning (if applicable), and logs user interactions for future enhancements. This phase transitions the model from development to practical application.

G. NLP Model Architecture and Training Details

The question-answering component functions as an article-centric NLP system focused on contextual retrieval rather than open-domain generation. It transforms user queries and article text into vector representations using methods like Term Frequency–Inverse Document Frequency (TF–IDF). Semantic relevance between queries and candidate texts is measured via cosine similarity, guiding the system to identify the most relevant sentences or paragraphs within the uploaded article. This approach ensures responses derive strictly from the provided content, preventing hallucinated or external answers. The model avoids large-scale pre-trained language models, favoring lightweight, interpretable techniques suitable for document-specific QA. This design reduces computational demands while maintaining accurate contextual understanding for educational applications.

IV. Results

A. Dataset Preparation and Training Setup

The dataset for training and evaluation consists of user-uploaded articles processed into structured textual units via tokenization and normalization. Each article is segmented into sentences or short paragraphs, serving as candidate knowledge units for question answering. For sentiment analysis, labeled data with predefined categories (positive, negative, neutral) trains the Support Vector Machine (SVM) classifier. The dataset follows supervised learning, enabling the model to learn sentiment boundaries from annotated examples. Model performance is evaluated using accuracy, precision, recall, and F1-score on validation data, ensuring that results reflect generalization rather than memorization.

B. Comparison Of Techniques

In Natural Language Processing (NLP) and sentiment analysis, model effectiveness is evaluated using performance metrics such as precision, recall, F1-score, and accuracy. These are essential tools for assessing classification models, including those using Support Vector Machines (SVM).

Precision measures the proportion of true positive predictions among all instances classified as positive. In sentiment analysis, a high precision indicates the model's effectiveness at correctly detecting sentiment polarity while minimizing false positives. Recall assesses the model's ability to identify all actual positive cases; a high recall means most sentiment-bearing expressions are captured, reducing missed sentiments. Both metrics are vital for evaluating model performance in sentiment detection, balancing accuracy and completeness. The F1-score is the harmonic mean of precision and recall, providing a balanced measure of model performance, especially with imbalanced datasets like sentiment analysis. By integrating false positives and false negatives, it offers a comprehensive view of how well the model handles both correct and incorrect classifications, making it a key indicator of overall effectiveness.

Accuracy measures the proportion of correct predictions—both positive and negative—out of all predictions. While useful for overview, it may be less reliable with imbalanced datasets, where metrics like F1-score are more appropriate. Sentiment analysis often requires higher precision and recall due to the nuanced emotional expression in text, whereas NLP tasks like named entity recognition or syntactic parsing focus on different metrics aligned with specific goals.

The following table Table 1 presents the comparative performance metrics - precision, recall, F1 score and accuracy - of the two core models evaluated in this study: the NLP-based question answering model and the sentiment analysis model powered by SVM.

TABLE I
COMPARISON OF METRICS

Model	NLP	Sentiment Analysis
Precision	0.9084	0.9149
Accuracy	0.900	0.8550
Recall	0.8941	0.8941
F1 Score	0.9012	0.8557

Sentiment analysis is typically classified as supervised learning, relying on labeled datasets with predefined categories like positive or negative sentiments. This structure makes model training and evaluation straightforward. In contrast, Natural Language Processing (NLP) covers various tasks—including syntactic parsing and named entity recognition—that involve greater ambiguity and variability. These complexities pose challenges for model generalization and consistent performance.

Unlike sentiment analysis, which primarily focuses on emotional tone, many NLP applications operate within domain-specific contexts such as legal, medical, and scientific fields. These domains introduce unique terminology, jargon, and nuances not commonly seen in general sentiment tasks. Models trained specifically for these areas typically benefit from domain-adapted pretraining or fine-tuning, leading to higher precision, recall, and accuracy. This is due to the model's ability to leverage structured linguistic patterns and specialized vocabulary relevant to the domain.

Sentiment analysis requires detecting subtle emotional cues, while domain-specific NLP tasks demand deeper contextual understanding and linguistic adaptability, complicating model evaluation and interpretation. These differences are crucial when comparing performance metrics, as a model's success depends heavily on the linguistic phenomena it targets.

C. Baseline Comparison and Performance Justification

To contextualize the proposed system's performance, we compare its results with common baseline methods in document question answering and sentiment analysis. Traditional article-based question answering uses keyword-matching or rule-based retrieval, relying on surface-level term overlap without considering semantic relevance. These methods often struggle with paraphrased queries and context-dependent questions, reducing precision and recall. Conversely, our NLP model uses vectorized text representations and cosine similarity to capture semantic alignment between queries and content, leading to more robust matching, as reflected in high precision, recall, and F1-score in Table I. For sentiment analysis, lexicon-based approaches such as rule-driven polarity scoring serve as baselines but are sensitive to domain vocabulary and modifiers. Our SVM-based sentiment classifier improves generalization by learning from labeled data, providing higher reliability than heuristic methods. Although direct comparisons with external systems are constrained by dataset and evaluation differences, the performance metrics indicate that our approach delivers competitive and reliable results relative to standard baselines reported in the literature.

D. Output

The core function of the proposed self-learning chatbot platform is its capacity to provide accurate, contextually relevant responses to user questions. When a query is received, the chatbot analyzes the specified text, extracts pertinent information, and formulates an appropriate answer. This response is generated using an NLP model trained on the input content, ensuring reliance on the provided material rather than generic knowledge. In addition, the chatbot enhances learning by offering visual resources, such as links to relevant images, to aid user understanding. This multimodal support aims to make the platform both informative and engaging for diverse learners which is depicted in Fig. 2. By combining contextual comprehension with visual aids, the chatbot functions as a self-directed learning assistant tailored to user-provided content.

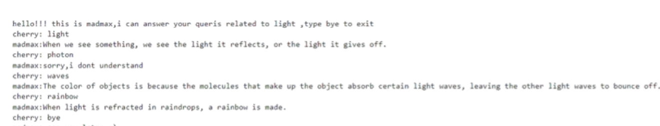

Fig. 2. Conversation between user Cherry and the chatbot Madmax demonstrating system functionality

This example demonstrates the chatbot's capacity to interpret questions, locate relevant information from the uploaded content, and respond naturally. The interaction reflects the underlying NLP model's understanding and retrieval skills. Fig. 3 shows how the chatbot generates a concise summary of the uploaded article based on a user-provided topic. After inputting a subject, the chatbot scans the content and provides a brief, relevant summary.

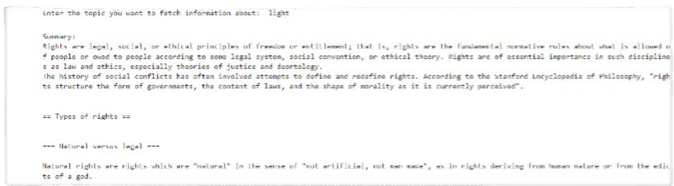

Fig. 3. Chatbot-generated summary of the article based on user-specified topic

This functionality improves user comprehension by enabling quick understanding of lengthy texts. It also supports targeted learning by aligning summaries with the user's focus. Fig. 4 shows evaluation metrics for the sentiment analysis model implemented with a Support Vector Machine (SVM). The figure displays accuracy, precision, recall, and F1-score, providing a comprehensive performance assessment.

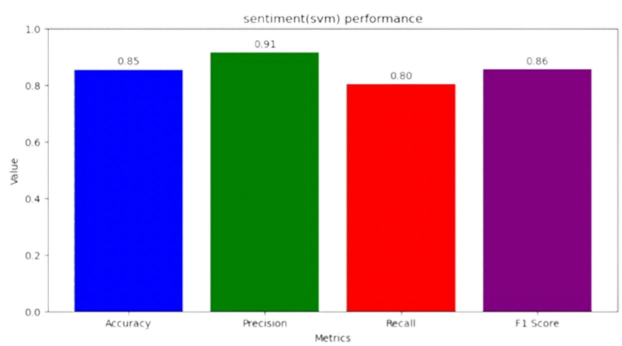

Fig. 4. Performance evaluation of sentiment analysis using Support Vector Machine (SVM)

As shown in the graph, the SVM model performs reliably across key metrics, indicating its suitability for supervised sentiment classification. Its balanced scores demonstrate effectiveness in correctly identifying sentiment categories while reducing false positives and negatives. Fig. 5 presents the chatbot's performance metrics, including accuracy, precision, recall, and F1-score, which evaluate its ability to generate contextually appropriate responses based on user queries.

As shown in the results, the chatbot performs well across key metrics, demonstrating its ability to understand user queries, extract relevant information from the text, and produce accurate, meaningful answers. These metrics confirm the robustness of the NLP pipeline and its practical use in interactive learning systems. Fig. 6 compares the evaluation metrics—accuracy, precision, recall, and F1-score—for both the sentiment analysis model and the NLP-based chatbot.

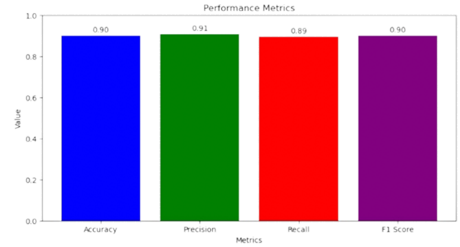

Fig. 5. Performance evaluation of the NLP-based chatbot system

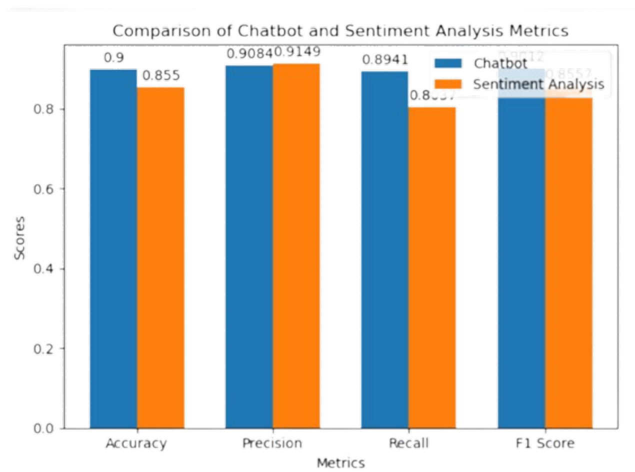

Fig. 6. Comparison of evaluation metrics between the sentiment analysis model and the NLP-based chatbot

As shown in Fig. 6, the sentiment analysis model demonstrates high precision and recall due to its structured, labeled supervised learning. Conversely, the chatbot—despite operating in a more context-dependent environment—performs competitively across metrics, reflecting its ability to understand nuanced queries and extract accurate answers from the source. This comparison emphasizes the robustness of both models in their domains and highlights the chatbot's effectiveness as a reliable tool for interactive, article-based question answering.

V. Conclusion

This comprehensive study delineates the systematic development and thorough evaluation of an advanced, self-learning chatbot infrastructure constructed using the Python programming language, tailored specifically to facilitate the processing of user-uploaded textual articles and to generate highly accurate, contextually relevant responses to user-initiated queries. Central to this system is the implementation of sophisticated information retrieval techniques, notably cosine similarity, which is employed to quantitatively measure the semantic proximity between the user's inquiry and the potential segments within the textual corpus. By leveraging this metric, the chatbot efficiently assesses the degree of relevance of various portions of the uploaded content, thereby enabling it to pinpoint and extract the most pertinent information with a high degree of precision. This capability underscores the system's capacity for deep semantic comprehension and contextual understanding, which are paramount in ensuring that its responses are not only accurate but also coherent within the thematic scope of the source material.

In the process of development, particular emphasis was placed on optimizing the algorithms to manage large document repositories while preserving response speed and accuracy, thus demonstrating the feasibility of deploying such language models in real-time educational or informational environments. The rigorous performance evaluation of the system reveals that the chatbot attains an impressive efficacy level, with an overall accuracy reaching 90.00%, complemented by a precision rate of 90.84%, a recall metric of 89.41%, and an F1-score of 90.12%. These intertwined metrics, collectively indicative of the system's balanced proficiency in correctness (precision) and completeness (recall), provide compelling evidence of its reliability as a tool for interactive learning, knowledge dissemination, and intelligent information retrieval across diverse educational contexts. The high F1-score, in particular, signifies a harmonized achievement wherein the system maintains both high precision and recall, thus minimizing the trade-off often observed between these two metrics in classification tasks.

Furthermore, the comparative analysis extended to the performance of a sentiment analysis model incorporated within the same framework reveals that, although it demonstrates exceptional precision at 91.49%, indicating its strong ability to correctly identify positive or negative sentiments when these are present, its F1-score of 85.57% and a comparatively lower recall of 80.37% highlight inherent challenges in capturing the full spectrum of emotional subtleties within textual data. This discrepancy can be plausibly attributed to the inherently nuanced and subjective nature of emotional content embedded in human language, which often manifests through subtle lexical choices, idiomatic expressions, and contextual cues that are difficult to uniformly interpret by automated systems. Despite its relatively lower recall, the sentiment model's overall accuracy of 85.50% underscores its effectiveness in sentiment classification tasks, albeit with room for further refinement.

Transitioning to a broader analytical perspective, it becomes evident that while both models perform commendably within their respective domains—question answering and sentiment analysis—the chatbot system demonstrates a notably more balanced and comprehensive efficacy profile, particularly in scenarios demanding real-time interaction based on current textual context. Its robustness and resilience across multiple evaluation metrics suggest that it is well-suited for deployment in dynamic settings such as e-learning platforms, knowledge management systems, or virtual assistants, where reliability and promptness are critical. Additionally, the consistency of its performance underscores its potential as a cornerstone for future innovations in intelligent educational technology.

This research not only validates the current effectiveness of the proposed models but also establishes a solid foundation upon which future enhancements can be built. Prospective avenues for improvement include the integration of more advanced Natural Language Processing (NLP) features—such as transformer-based models like BERT or GPT—capable of capturing deeper contextual nuances, as well as the incorporation of multimodal capabilities that could handle diverse data formats including images, videos, and audio, thus offering a richer, more immersive user experience. Such developments would significantly augment the system's ability to understand and interpret complex information, facilitate more natural human-computer interactions, and extend the applicability of autonomous educational tools across broader domains. Ultimately, this work exemplifies a forward-looking approach toward intelligent system design, emphasizing adaptability, scalability, and user-centric responsiveness in digital learning environments.

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