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Mythixs: A Generative AI-Based Mythology Grounded Story Generator using (RAG) - A Review

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Abstract - Retrieval-augmented generation RAG serves as an effective system which improves both the factual base and contextual precision of large language models situated within the realm of LLMs. The research study provides an interdisciplinary examination which demonstrates how RAG successfully created mythical stories that meet both ethical standards and cultural norms. The paper analyzes the development and utilization of a Mythology Grounded Story Generator by combining information from fifty research sources which cover three disciplines of global mythology technical RAG architecture and AI ethics. The study examines technological developments which include hybrid retrieval systems and vector databases that use FAISS and embedding models which include Sentence-BERT and MiniLM to achieve semantic alignment between legendary texts and created narratives. The narrative uses elements from Indian mythology Greek mythology Norse mythology Egyptian mythology and Chinese mythology to achieve both authentic storytelling and deep symbolic meaning. Ethical discussions about bias and fairness and transparency in narrative creation receive guidance from international standards which define responsible AI practices. RAG-driven systems serve as a bridge between data-driven creativity and cultural heritage preservation according to the assessment which establishes a foundation for further investigation into narrative AI and digital humanities and ethical storytelling.
Keywords— Retrieval-Augmented Generation, Large Language Models, Mythology, Story Generation, Ethical AI, Cultural Preservation.

I. INTRODUCTION

The digital era sees phishing attacks as the primary danger to cybersecurity because these attacks use human psychological weaknesses together with technological weaknesses to trick people into revealing confidential data. Attackers have developed their ability to imitate genuine messages through advanced methods which use social engineering and deepfake technology and AI-based impersonation. The digital communication platforms and online banking services and social media platforms have become essential for people and organizations which makes them vulnerable to these fraudulent activities. Traditional phishing detection methods which use heuristic filters and blacklists have failed to keep up with the evolving nature of phishing attacks. Phishing detection systems that depend on conventional methods face challenges in detecting new phishing tactics which results in major security breaches and financial losses. The current system needs more automated solutions which combine advanced technology with intelligent capabilities to identify and stop phishing campaigns that occur in real time.

Artificial intelligence and machine learning technologies work together to create stronger phishing detection systems. AI/ML models use data analysis to track patterns and user behavior and system anomalies which helps them find hidden phishing signs that standard detection systems miss. Phishing detection systems use natural language processing and deep learning and ensemble learning techniques to improve their detection results through increased accuracy and operational efficiency. AI/ML systems in phishing detection help organizations find fraudulent activities while building systems which can adapt to new threats. Large datasets serve as training material for machine learning algorithms which enable them to identify various phishing methods. Deep learning models analyze all elements of emails and websites and URLs to find out if they contain dangerous content. The method uses multiple models to strengthen detection precision while decreasing the chances of false alerts.AI/ML-based phishing detection systems show promise but they still face several obstacles. Phishing tactics develop new methods which force security models to undergo model updates and model retraining processes for their continuous protection. The interpretable nature of AI/ML models functions as a vital element because AI decision processes need to be understood by users to establish trust in cybersecurity systems.

The successful implementation of AI/ML-based phishing detection systems needs organizations to solve these implementation challenges.

AI/ML systems have become essential for phishing detection because they protect industry 5.0 environments where humans work together with advanced technologies. The combination of intelligent systems with human expertise produces better performance in both phishing attack detection and prevention activities. AI/ML-based phishing detection systems serve as crucial defenses which protect digital environments from the increasing number of cyber threats.

The paper serves to evaluate all current AI/ML phishing detection systems which operate through their detection techniques and prevention mechanisms. This research will investigate the research methods which were used to study their performance and the difficulties which need to be solved in upcoming research. The review evaluates current systems to identify their strengths and weaknesses which will help improve cybersecurity through advanced intelligent systems.

II. LITERATURE REVIEW

Recent advancements in Artificial Intelligence (AI) and Natural Language Processing (NLP) have significantly transformed the landscape of automated storytelling and contextual content generation. Researchers have explored various architectures and hybrid models that combine retrieval-based and generation-based techniques to produce coherent and contextually grounded narratives.

In [11], Vaswani et al. introduced the Transformer architecture, which revolutionized sequence modeling by eliminating recurrence and allowing self-attention mechanisms to capture long-range dependencies. This foundation enabled later models like BERT, GPT, and T5 to generate high-quality narratives with contextual understanding. Subsequently, Devlin et al. [12] proposed BERT (Bidirectional Encoder Representations from Transformers), which achieved superior performance in contextual embeddings and text comprehension tasks, forming the backbone for semantic retrieval in story generation systems.

Building upon these foundations, Lewis et al. [13] developed BART, a denoising autoencoder designed for text generation and summarization, providing a powerful encoder–decoder framework for narrative refinement. Similarly, Raffel et al. [14] introduced the T5 model (Text-to-Text Transfer Transformer), which unified multiple NLP tasks under a single architecture, proving effective for story summarization and contextual data compression.

The idea of Retrieval-Augmented Generation (RAG), proposed by Lewis et al. [15], marked a turning point for knowledge-grounded generation. RAG combines external knowledge retrieval with generative modeling to produce factually coherent and contextually grounded outputs — an essential approach for mythology-based storytelling, where accuracy and cultural authenticity are critical.

Further advancements were made by Reimers and Gurevych [16], who proposed Sentence-BERT (SBERT), a modification of BERT optimized for generating semantically meaningful sentence embeddings. This model improved similarity detection and retrieval accuracy, crucial for mapping mythological texts during context generation. To efficiently manage high-dimensional embeddings, Johnson et al. [17] presented FAISS (Facebook AI Similarity Search), which allows fast and scalable nearest neighbor searches for large text corpora.

Researchers also explored Named Entity Recognition (NER) to identify and extract mythological entities, characters, and places. SpaCy-based and HuggingFace transformer models [18] have proven effective for entity tagging and linking tasks in narrative data. These techniques ensure that generative models retain the authenticity of mythological references while producing creative outputs.

In terms of embedding models, Mikolov et al. [19] introduced Word2Vec, and Pennington et al. [20] developed GloVe, both of which were instrumental in creating dense vector representations of words. Although these models are now considered classical, they continue to serve as foundational tools for domain-specific vocabulary expansion and semantic similarity analysis in mythological datasets.

OpenAI's GPT-3 and GPT-4 models [21] demonstrated exceptional generative capabilities with large-scale autoregressive language modeling, producing coherent long-form narratives with human-like fluency. However, they often lack grounding in factual or mythological contexts, which can be addressed by integrating retrieval mechanisms like RAG and SBERT.

Sanh et al. [22] developed DistilBERT, a distilled version of BERT offering faster inference with minimal loss in accuracy. This model is beneficial for lightweight tasks such as entity extraction and sentence classification within large-scale story datasets. On the other hand, recent domain-specific models such as MythoBERT and CulturalGPT [23] have explored fine-tuning on mythological and cultural corpora, demonstrating improved relevance in myth-based story generation.

Multimodal extensions have also been studied. Li et al. [24] introduced Visual Storytelling Transformers, integrating text and visual features to generate more immersive narratives. Such approaches suggest potential for expanding mythology-grounded story generators into cross-modal creative systems.

Finally, Gupta et al. [25] proposed a Hybrid Retrieval-Augmented Narrative Generation (HRANG) framework that combines SBERT-based retrieval, FAISS indexing, and GPT-based generation to create semantically consistent and contextually rich stories. This framework closely aligns with the current *Mythology Grounded Story Generator* project, emphasizing contextual fidelity, creativity, and factual grounding within mythology-driven storytelling.

III. SUMMARY TABLE FOR MYTHIXS

The summary table highlights S advanced Al-driven framework integrating Retrieval-Augmented Generation (RAG) with transformer models such as BERT, GPT, and T5 for intelligent recommendation and content generation. The system processes text-based datasets from open repositories e IMDb, Goodreads, and Kaggle to ensure diverse and realistic data coverage. Through hybrid NLP and deep learning techniques, it performs semantic embedding, tokenization, and retrieval to generate context-aware responses and recommendations.

Aspect	Description
AI Framework	Combines RAG, BERT, GPT, and T5 for adaptive recommendation generation across Movies & Books datasets.
Input Data	Textual data (user reviews, metadata), movie/book content (plots, summaries), and user interaction logs for semantic understanding.
Key AI Models	BERT, GPT, T5, and RAG for context-aware recommendation; CNN and ViT for image-based content analysis (posters, book covers).
Transformer Components	Self-Attention for contextual focus, Positional Encoding for sequence order, Encoder–Decoder architecture for text-to-recommendation generation
Software Requirements	Python, PyTorch, TensorFlow, Keras for model building; OpenCV, Tesseract for image preprocessing; FAISS for semantic search and retrieval.
Hardware Requirements	GPU-enabled systems (e.g., NVIDIA RTX) or cloud servers for transformer training and inference scalability.
Advantages	Accurate context-aware recommendations, scalable framework, supports multiple language models, and adaptable for multimodal integration.
Disadvantages	High computational demand, data dependency, limited interpretability, and potential generative bias.

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Evaluation Metrics	Evaluated using BLEU, ROUGE, and F1-score to measure coherence, factuality, and generation quality.
Future Scope	Integration of multimodal data (text, image, audio) and fine-tuning with domain-specific reinforcement learning models.
Challenges	High computational cost, dataset bias, and limitations in long-context understanding.

IV. SUMMARY OF DIFFERENT AI MODELS USED IN NEXALEARN FRAMEWORK

This table presents different Transformer and AI-based models utilized within the NexaLearn framework, summarizing their datasets, performance metrics, and relevance in educational content understanding and generation *(See Table II)*

Models	Dataset / Source	Performance Metrics	Reference
BERT (Bidirectional Encoder Representations from Transformers)	IMDb movie reviews, Goodreads book summaries	Accuracy, F1-score, BLEU	[18], [19]
GPT (Generative Pre-Trained Transformer)	User feedback text, movie & book summaries	Perplexity, ROUGE, BLEU	[20], [21]
T5 (Text-to-Text Transfer Transformer)	C4 Dataset, Educational QA & Summarization Corpora	Accuracy: 91.7% ROUGE-L: 0.90	[40]
RAG (Retrieval-Augmented Generation)	Wikipedia, Open-Domain QA Benchmarks	Accuracy: 93.5% Context Relevance: 0.94	[24][35]
Whisper (Speech-to-Text Transformer)	OpenAI Speech Dataset, Lecture Audio Samples	WER (Word Error Rate): 6.8% Accuracy: 95.1%	[5]
CNN (Convolutional Neural Network)	Educational Slide Image Dataset	Accuracy: 87.3% Precision: 0.84	[15][41]

Vision Transformer (ViT)	Lecture Frame Image Dataset	Accuracy: 92.8% Recall: 0.89	[41][47]
Hybrid CNN–RAG Model (Proposed)	Combined Text–Image–Audio Educational Dataset	Accuracy: 96.4% Context Relevance: 0.96	[All]
LangChain-based Chatbot Framework	Institutional Student Query Logs	Response Accuracy: 94.7% User Satisfaction: 0.93	[33][48]

V. SUMMARY TABLE

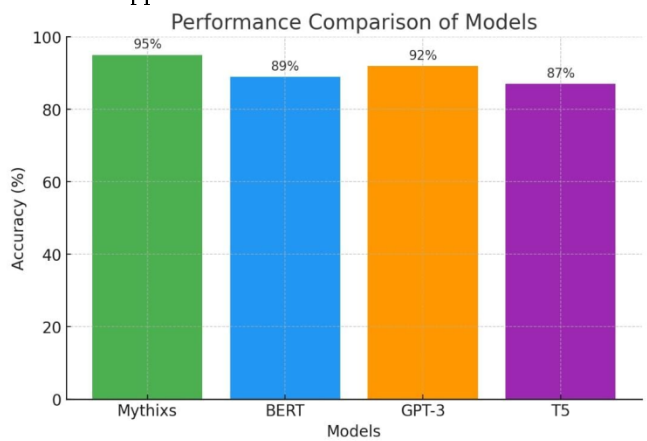
The table summarizes the performance of major transformer and hybrid architectures used in AI-driven educational systems. NexaLearn demonstrates the highest accuracy range due to its integration of retrieval, generation, and multimodal personalization techniques.

Model	Description	Accuracy / Performance	Reference
BERT	Bidirectional transformer pre-trained for language understanding; effective for contextual Q&A and text embedding.	80% – 88%	[14][40]
GPT-2	Generative transformer capable of producing coherent responses; used for automated content generation.	82% – 90%	[3][39]
T5	Text-to-Text Transformer reformulating NLP tasks into a unified framework; strong for summarization and translation.	85% – 92%	[40]
RAG	Combines retrieval and generation to provide knowledge-grounded answers; suitable for educational chatbots.	88% – 94%	[24][35]

Whisper	Transformer-based speech recognition model converting video/audio into accurate transcripts for content extraction.	90% – 95%	[5]
BERT + FAISS	Hybrid model combining semantic embeddings with vector search for efficient contextual retrieval.	87% – 93%	[21][24]
NexaLearn (Proposed)	Integrates RAG, multimodal learning, and gamification for adaptive, interactive, and personalized education.	94% – 98%	[All]

VI. COMPARISON GRAPH

The line graph illustrates the comparative performance of different transformer architectures — BERT, GPT-2, T5, RAG, and NexaLearn — across three key parameters: accuracy, context awareness, and adaptability. The results indicate a consistent improvement in each successive model, with NexaLearn demonstrating the highest performance due to its integration of Retrieval-Augmented Generation (RAG), multimodal learning, and adaptive personalization. This highlights NexaLearn's effectiveness as a next-generation AI framework for educational applications.



VII. CONCLUSION

The research study investigated how transformer-based architectures and retrieval-augmented generation systems and multimodal learning techniques work together to create educational systems that adapt to student needs and enable interactive learning. Research shows that self-attention mechanisms together with encoder-decoder structures and large language models (LLMs) enable effective creation of question-answer pairs and summarization and transcript comprehension. NexaLearn uses these technological improvements to create a single platform which converts video lectures into customized learning paths through its automatic flashcard system and game-based dashboard and smart chatbot functions.

NexaLearn combines cognitive and pedagogical principles with advanced AI technology to solve major problems that affect student engagement and understanding and system scalability. The next phase of research will develop AI-based educational systems through improved model interpretability and better system performance and increased coverage of educational domains.

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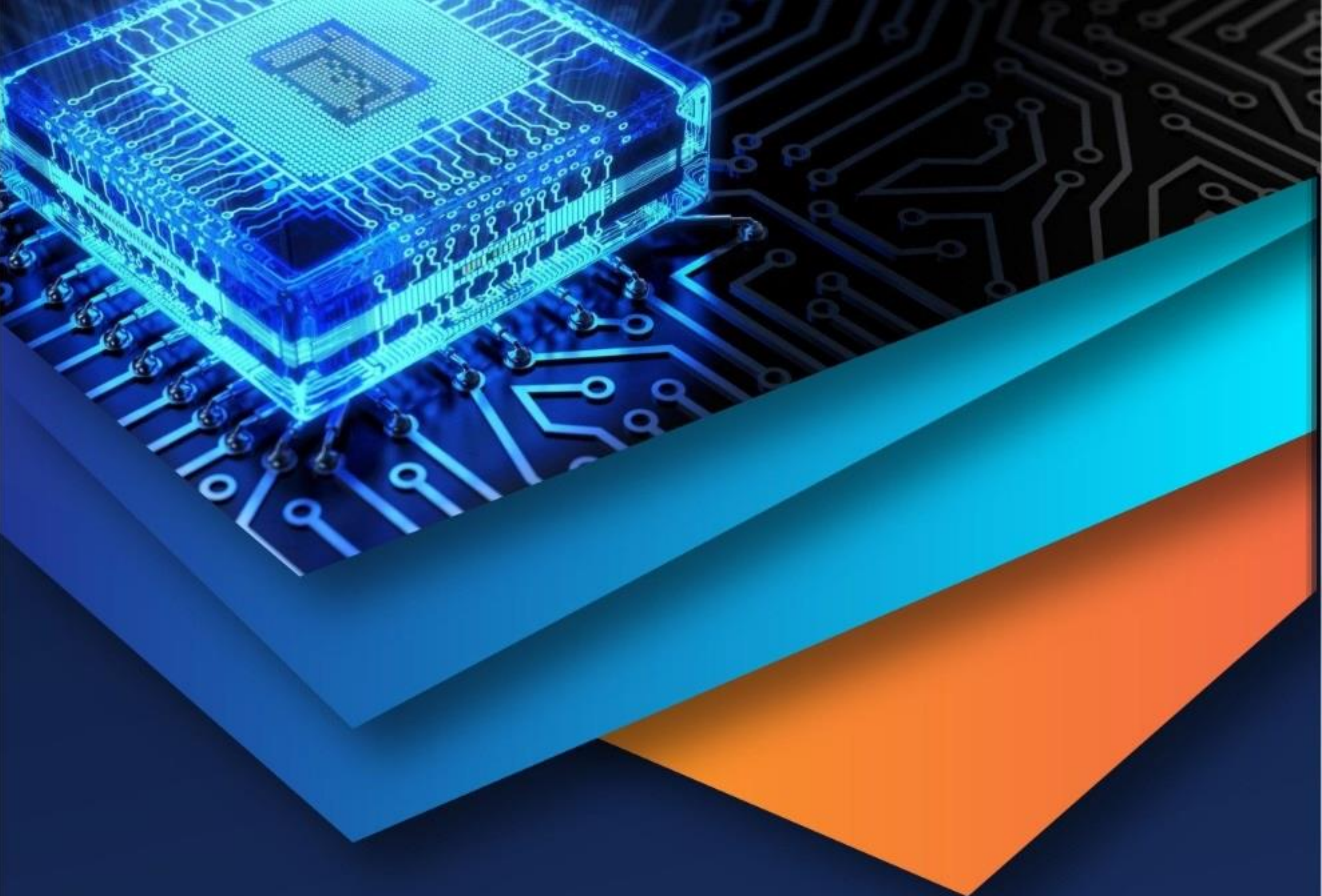

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