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Optimizing Metadata Structures for Enhanced Search and Retrieval in Digital Libraries

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Abstract- **Purpose: Research aims to enhance search and retrieval in digital libraries by optimizing traditional metadata structures using deep learning. It addresses the semantic limitations of conventional metadata in handling unstructured full-text documents, enabling more precise and context-aware search outcomes. Methodology: A novel Artificial Gorilla Troops Optimizer-driven Attention-based Recurrent Neural Network (AGT-ARNN) model was developed to extract and classify high-quality semantic metadata from digital library documents. A comprehensive full-text dataset with manually annotated metadata was used. Preprocessing involved tokenization, lemmatization, and stemming to clean and standardize the text, followed by Word2Vec embedding to retain contextual semantics. This approach captured deeper syntactic and semantic dependencies, boosting the model's understanding of complex document structures. All phases of data processing, model construction, and evaluation were carried out using Python. Results: The AGT-ARNN model demonstrated superior performance with an accuracy of 97%, precision of 90%, recall of 93%, and F1-score of 95%, outperforming methods. It significantly improved retrieval speed and relevance, creating semantically rich metadata for digital library systems. Conclusions: The proposed framework effectively transforms digital libraries into intelligent systems by automating the generation of deep, semantically enhanced metadata. These findings support scalable, real-time, user-centered information access in next-generation knowledge environments**.

Keywords: **Digital Libraries, Information Retrieval, Metadata, Semantic Search, Text Lines Artificial Gorilla Troops Optimizer-driven Attention Based Recurrent Neural Network (AGT-ARNN)**

I. Introduction

The rapid expansion of digital libraries has increased the need for effective organization, discovery, and retrieval of information and knowledge (Farkhari et al., 2024; Al-Assadi & Kaabi, 2024). Metadata provides structured, descriptive information about resources to support their identification, organization, management, and use (Xu & Shang, 2024). Metadata structures, while essential, frequently experience heterogeneity, inconsistency, and semantic inadequacy, resulting in poor search results and impaired interoperability (Bai et al., 2024; Bouche et al., 2021). As digital collections have grown in format, scale, and complexity, the opportunity to develop improved metadata structures that are scalable and have deeper semantic structure has become more critical (Jha, 2023; Halim et al., 2024). Metadata optimization encompasses the refinement of schema design, the enhancement of metadata quality, and the integration of advanced technologies to support more precise retrieval and improved user experience (Moses et al., 2023). The implementation standards, such as Dublin Core, Metadata Object Description Schema (MODS), and Metadata

Encoding and Transmission Standard (METS), as well as emerging semantic web technologies, such as Resource Description Framework (RDF) and Web Ontology Language (WOL) have been proven to support improved discoverability and interoperability for digital resources (Wang et al., 2025). Furthermore, applying linked data principles allows for richer and more interconnected metadata networks that facilitate context-aware retrieval and knowledge discovery. The areas of machine learning and Natural Language Processing (NLP) have also facilitated metadata that not only enhances the metadata dynamically but also supports automated classification, thus reducing time spent manually and reducing inconsistencies (Enlevi & Masruri, 2023). Protocols such as the Open Archives Initiative Protocol for Metadata Harvesting (OAI-PMH) provide an opportunity for metadata harvesting and aggregation over distributed repositories, which aim to provide greater visibility and integration of resources. However, concerns about metadata quality, interoperability among multiple metadata standards, and general automation vs. human control remain (Huang et al., 2023). Efficient metadata structures are vital for enhancing a digital library's functionality, discoverability, and long-term usability (Igwechi Wiche, 2023). A standards-based approach ensures accurate retrieval and supports ongoing innovation in digital information systems (Vasishta et al., 2024). The aim of the research proposes a method that leverages a deep learning-based AGT-ARNN model to generate high-quality semantic metadata from full-text documents, aiming to improve search precision, retrieval efficiency, and user experience in digital libraries (Asl & Naderi, 2016).

A. Key Contributions

- A diverse dataset of 500 annotated entries from Kaggle, spanning various domains, enables semantic metadata classification and supports training deep learning models for digital libraries.
- Text preprocessing includes tokenization, lemmatization, and stemming to reduce linguistic variability, enhance semantic consistency, and prepare structured inputs for accurate metadata classification in digital libraries.
- Word2Vec transforms words into dense vectors capturing semantic relationships, enabling deep learning models to understand the context and enhance metadata extraction from complex full-text documents.
- The AGT-ARNN model integrates attention-based RNNs with adaptive optimization to classify semantically rich metadata, significantly improving accuracy, precision, and retrieval efficiency in digital library environments.

Organization of the Research: Section II reviews related work on semantic metadata and deep learning in digital libraries. Section III outlines the proposed methodology, including preprocessing, word embedding, and the AGT-ARNN model. Section IV presents experimental results, Section V provides a discussion, and Section VI concludes the research with suggestions for future work.

II. Related Work

Wang & Yu, (2024) investigated intelligent information processing technologies in digital libraries utilizing Deep Learning (DL). Convolutional Neural Networks (CNN) was used to gather and analyze digital library data to increase efficiency and accuracy. The system was capable of automatically identifying and categorizing data, extracting keywords, and carrying out activities like recommendations and summaries. Additionally, it constantly improves the efficiency of information processing through learning and knowledge transfer.

Wang & Jia, (2024) investigated how DL, large data, and image processing could be combined in digital libraries. It highlights problems, including inadequate multimedia resource arrangement and underuse of cross-modal correlation. The research suggested a DL-based cross-media semantic search architecture that achieves an 11.53% improvement in search performance.

Dolezal et al., (2024) suggested a variety of DL techniques for histopathology, including digital pathology, which was supported by the Slideflow library. Effective stain normalization, and feature creation, with a quick whole-slide approach for distributing model training, were all included. The framework-agnostic data processing pipeline provides quick experimentation with new methodologies, while the graphical user interface offers real-time viewing on a variety of hardware devices, including Raspberry Pi, allowing for efficient testing with novel designs.

Morid et al., (2023) analysis of an extensive assessment of research on DL techniques for healthcare predictive analytics has been released by the Association for Computing Machinery Digital Library (ACM) Digital Library. DL methods were excellent at handling periodic extremely complex problems in medical data, allowing for the acquisition of nonlinear relationships and helpful representations.

Increasingly, ontologies a method of representing knowledge were being combined with DL algorithms. Nevertheless, current ontology APIs, such as Jena and OWL API, were unable to convert ontologies into forms that were appropriate for DL-based applications. To solve this, DeepOnto, a Python package, was developed, which includes a core ontology processing module and a set of tools and algorithms for ontology engineering tasks, such as alignment and completeness (He et al., 2024).

Jin et al., (2023) proposed that DL was a highly specialized field that necessitates experience with software tools, such as TensorFlow and Keras, and model construction and optimization best practices. With a few lines of code, inexperienced users handle common ML challenges due to

AutoKeras, an automated ML toolkit that streamlines selecting models and hyperparameter tweaking.

DL was an extremely specialized field that necessitates knowledge of model design, optimization best practices, and software applications, such as TensorFlow and Keras. AutoKeras, an automated ML package, automates selecting models and hyperparameter tweaking, allowing even beginner users to address common ML challenges with a few lines of code (Deng et al., 2023).

Defects in the DL library affect downstream applications, requiring dependable systems. FuzzGPT, a technology that primes Large Language Models (LLMs) to generate novel fuzzing programs, covers this void. In identifying 76 defects, comprising 49 unknowns, and 11 high-priority bugs or vulnerabilities in security (Verma, 2023), it beats TitanFuzz, proving its applicability and generalizability.

A subset of human cognition patterns, trends, and biases, AI-based data has a big influence on the socio-digital traces of human activity. It can adjust sustainable aims with ease of language convergence, improving the context's substance and application (Hamad et al., 2023). AI-powered digital chatbots with data authenticity were enhancing digital library concepts around the clock.

Hamad et al., (2024) examined how academic libraries have moderate obstacles when introducing smart services, according to research conducted in Jordan. These obstacles include reluctance to change, worries about privacy and confidentiality, and budgetary difficulties involving inadequate facilities and staff training. These difficulties have a detrimental impact on the quality of smart services provided, underscoring the necessity of better preparation and execution.

III. METHODOLOGY

The proposed method relies on deep learning and metaheuristic optimization to extract metadata from full-text files. The text preprocessing will include tokenization, lemmatization, and stemming. The dataset will consist of annotated metadata lines from a digital library repository. However, when it comes to text data, it will be put into a word2vec and then those embeddings will be fed into the ARNN, where the ARNN will learn to recall dependencies in context. The AGTO algorithm will optimize the ARNN parameters, resulting in precise metadata classification while maintaining the contextual integrity of semantics, resulting in better organization and utilization of digital libraries. Fig.1 presents the working flow of the research.

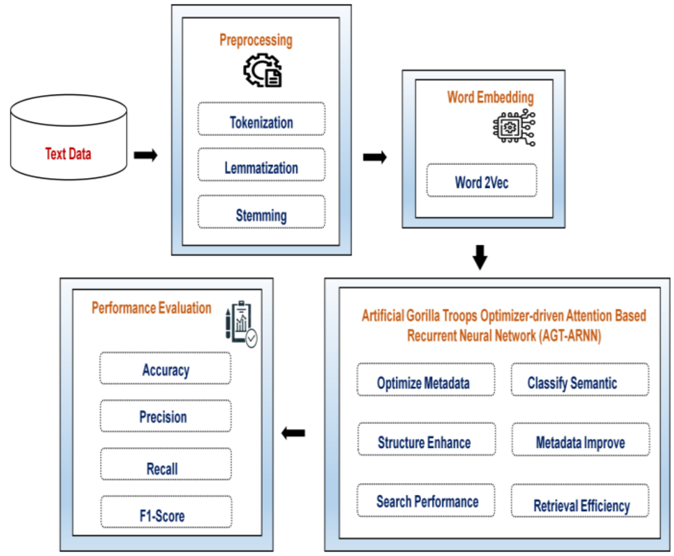

Fig. 1 Methodology Flow

A. Dataset

A dataset of 500 annotated text entries, sourced from Kaggle (https://www.kaggle.com/datasets/ziya07/metadata-dataset-for-digital-libraries/data), is used to create machine learning models for semantic metadata extraction and text classification. Table I presented the sample data, each entry contains a Semantic Label and a Numeric target (0–4), consisting of the domains of medical imaging, quantum supply chain optimization, and document classification. The goal is to improve upon the structure around the metadata and to improve classification accuracy, ultimately providing better search and retrieval capabilities in digital libraries or other content-heavy environments to take advantage of semantic search capabilities.

TABLE I. SAMPLE DATA

Text	Metadata_line	Target
Reinforcement learning models for automating metadata labeling and classification. Example 1 on metadata and machine learning.	medical image classification	0
Machine learning for personalized recommendations based on user preferences. Example 7 on metadata and machine learning.	quantum supply chain optimization	1
Reinforcement learning models for automating metadata labeling and classification. Example 13 on metadata and machine learning.	document classification with attention	2
Deep learning models applied to document classification and natural language processing. Example 12 on metadata and machine learning.	semantic metadata extraction	3
Neural networks for improving medical diagnoses through image analysis. Example 19 on metadata and machine learning.	knowledge graph for semantic search	4

B. Preprocessing

Preprocessing converts raw textual data into a structure using tokenization, lemmatization, and stemming. This process minimizes some of the linguistic variability, improves some semantic consistency in the documents, and prepares these input sequences for classifying metadata into digital library systems.

1. Tokenization

Tokenization is a necessary preprocessing step that breaks continuous text into discrete lexical units. As an example, the sentence from the dataset "Quantum supply chain optimization is enhanced through attention-based neural encoding." is tokenized into ["Quantum", "supply", "chain", "optimization", "is", "enhanced", "through", "attention", "based", "neural", "encoding"]. This process allows DL models to analyze the syntactical and semantic structure of complex technical phrases, which allows for accurate metadata extractions, typically in algorithm-run digital library environments.

2. Lemmatization

Lemmatization is a normalization technique that consolidates inflected word forms to their dictionary base forms based on linguistic and contextual clues. In the dataset example "The architecture retrieves optimization parameters through embedded learning layers," the inflected word forms "retrieves" and "parameters" would be lemmatized to "retrieve" and "parameter," respectively. Lemmatization as a process of normalization limits lexical variation without losing the semantic meaning of the terms used and consistency in using metadata terminology. This is a common pre-processing step that will improve the generalizability of models and enhance the semantic consistency of classes during classification in information retrieval approaches in digital libraries.

3. Stemming

Stemming eliminates affixes to reduce words to their morphological roots with little regard for meaning or grammar. For the dataset phrase, “Classification algorithms improve metadata generation efficiency,” stemming would result in "classified" for "classification" and "efficient" for "efficiency." Although less accurate and precise than lemmatizing, stemming reduces vocabulary size and dimensionality effectively. Both of these help with runtime performance and meaningful feature encoding for deep learning models for metadata generation from scientific full-texts.

C. Word Embedding Using Word2Vec

Word2Vec provides a neural embedding technique for embedding words and generating dense, continuous vector representations of words capturing their contextual and semantic relationships. This is an important way to represent text as a number to feed machine learning models. The word2vec generates word representations by using the Skip-gram architecture, which is an effective method for predicting the words surrounding a word in written languages. The objective function of the Skip-gram approach optimizes the logarithmic probability of having all the context words in a predetermined window size of a given center word, given as Equation (1):

$$\mathcal{L} = \sum_{s=1}^{S} \sum_{-i \le l \le i, l \ne 0}^{s} \log O(x_{s+l} | x_s) \tag{1}$$

In this expression, S represents the total number of words in the corpus, while x_s denotes the current or center word at position$s$. The term x_{s+l}refers to a context word that appears l positions away from the center word within a fixed-size window. The parameter i defines the size of this context window on either side of the center word. The conditional probability $O(x_{s+l}|x_s)$quantifies the likelihood of the context word occurring, given the center word. This probability is in Equation (2) using a softmax function:

$$\left(x_p | x_j\right) = \frac{\exp\left(u_{x_p}^{\mathrm{T}} . u_{x_j}\right)}{\sum_{x=1}^{|U|} \exp\left(u_{x}^{\mathrm{T}} . u_{x_j}\right)} \tag{2}$$

In this equation, $u_{x_j}^T$ is the vector representation of the input (center) word and $u_{x_p}^T$ is the vector of a surrounding context word. The variable $|u|$indicates the total size of the vocabulary in the corpus. By learning such contextual representations, Word2Vec enables efficient semantic encoding of textual content, improving the accuracy of search and retrieval tasks in digital library systems.

D. Adaptive Gorilla Troops Optimized Attention-Based Recurrent Neural Network (AGT-ARNN) for Enhanced Metadata Classification in Digital Libraries.

AGT-ARNN combines AGTO and an ARNN to deepen metadata classification in digital libraries. In this view, AGTO is harnessed as a tool for tensor hyperparameter search while optimizing network architecture to provide value, robustness, and guaranteed convergence and accuracy across complex full-text documents. The attention mechanism can identify semantically relevant tokens of the chosen input to fully contextualize complex documents; while the use of recurrent layers captures temporal information and dependencies common to structured documents. AGT-ARNN supports the conversion of knowledge work through greater efficiency in metadata extraction, sophisticated searching and retrieval mechanisms in digital repositories, and enhanced overall end-user efficacy.

1. Recurrent Neural Networks (RNNs)

RNNs belong to a category of DL models that can be applied to sequence data by retaining contextual memory via internal loops. It leverages RNNs in this research, itcan process tokenized and embedded full-text inputs, maintaining all temporal and semantic dependencies needed to recognize quality lines of metadata. RNNs differ from feedforward networks because RNNs retain information from the previous time step, so they model linguistic patterns across sentences. RNNs' ability to learn sequences allows the system to apply more accurate and context-relevant metadata classifications, furthering the overall effectiveness of semantic retrieval in digital library information systems.

2. Attention Mechanism

To improve neural networks by allowing models to focus selectively on relevant sections of input sequences while being processed. In this work, attention is introduced at the recurrent architecture stage to weight document tokens across full-text documents, with a preference for terms that will support semantics for metadata. By selectively and actively focusing their attention, the model improves both interpretability and accuracy, as it dynamically associates input features with their contextual significance. In this way, almost nuanced dependencies throughout long sequences can occur, not only enhancing the metadata classification accuracy but also semantically informative summaries to support the searching and retrieving process in a digital library environment.

3. Sequential Modeling Using Attention-Based Recurrent Neural Networks (ARNN)

RNNs have shown significant capacity in learning on sequential data. However, they have significant limitations due to multiple reasons, the vanishing gradient problem, as RNNs lack a mechanism for learning long-term dependencies in the data. Additionally, RNNs consider the sequence of tokens in a fixed order and are equally sensitive to each token, placing the same level of importance on all tokens semantically because they do not use context – both of these features shared before NLP tasks like the classification of metadata, which benefits from prior semantic importance. These restrictions create barriers to the employment of standard RNNs, which become ineffective in their ability to capture rich context-aware metadata from long, unstructured full-text documents, which are common in digital libraries. To address these limitations, this research takes advantage of an ARNN in this case. The ARNN is an enhanced RNN, which uses an attention mechanism to weigh the relevance of each input token in connection with the current prediction dynamically. This selective focus allows the model to preserve and utilize semantically important information across long sequences, thereby improving the accuracy and interpretability of metadata classification. Mathematically, at each decoding time step s, the ARNN computes a context vector d_s as a weighted sum of all encoder hidden states g_j, expressed as Equation (3):

$$d_s = \sum_{j=1}^{S} \alpha_{s,j} . g_j \tag{3}$$

Srepresents the total number of tokens in the input arrangement, and g_j denotes the hidden state of the RNN corresponding to the j^{th}token. The attention weight $\alpha_{s,j}$indicates how much attention the model assigns to the j^{th} word while generating the output at time s. These attention weights $\alpha_{s,j}$are computed using a softmax function applied over alignment scores $f_{s,j}$, which quantify the similarity between the decoder hidden state g_s and each encoder hidden state $g_j$using Equation (4):

$$\alpha_{s,j} = \frac{\exp(f_{s,j})}{\sum_{i=1}^{S} \exp(f_{s,j})} \tag{4}$$

The alignment score $f_{s,j}$is typically calculated as a dot product between the decoder hidden state g_s and the encoder hidden state g_j, projected by a learnable weight matrix X_b, as follows in Equation (5)

$$f_{s,j} = g_s^{\mathsf{T}} X_b g_j \tag{5}$$

In this preparation, g_s is the hidden state at time step s from the decoder, g_j is the encoder's hidden state at position$j$, and X_b is a trainable matrix that converts one hidden state into the space of the other for similarity computation. The ARNN can dynamically extract and highlight contextually significant metadata from full-text sequences to the attention mechanism, which eventually supports more accurate search and retrieval strategies in digital library systems.

4. Adaptive Gorilla Troops Optimized (AGTO)

The AGTO is utilized in this research to optimize the hyperparameters of an ARNN model to improve semantic metadata classification in digital libraries. In AGTO, nature is used as an inspiration, drawing the processes from the natural behavior of gorilla troops that would include actions like migrating to an unknown area, moving to a known high-potential area, and following other successful solutions. These strategies help guide the optimizer as it explores the parameter space in the most efficient manner possible to optimize model performance. Instead of considering optimization purely in theoretical terms, AGTO is being used practically to optimize the architecture of the ARNN model (which includes learning rate, dropout, and layer structure) to increase the model's ability to extract the relevant metadata lines from complex full-text documents. As a result, the AGTO-enhanced ARNN model hypothesis semantically rich metadata structures that increase the efficiency of search and retrieval procedures within digital library environments using Equations (6- 11).

$$X(it+1) = \begin{cases} (UB - LB) \times q_1 + LB & rand < o \\ (q_2 - D) \times W_q(it) + K \times G & rand \geq 0.5 \\ W(l) - K \times \left(K(it) - GX_q(it)\right) & rand < 0.5 \\ \quad +q_3 \times \left(W(it) - GX_q(it)\right)) & \end{cases} \tag{6}$$

$$D = E \times \left(1 - \frac{it}{Max\_it}\right) \tag{7}$$

$$E = \cos(2 \times q_4) + 1 \tag{8}$$

$$K = D \times k \tag{9}$$

$$G = Y \times W(it) \tag{10}$$

$$Y = [-D, D] \tag{11}$$

The AGTO formulation $GX(it)$, and $GX(it+1)$ denote the current and updated position vectors of a gorilla at iterations, respectively. The terms UB and LB represent the upper and lower bounds of the search space. Parameters $q1, q2, q3, q4, q5$ are random numbers uniformly distributed within the range [0, 1], which introduce stochastic behavior into the search process. The term ω is a prospect threshold that governs the assortment of exploration strategies. $D$is a dynamic control parameter that decreases linearly over iterations, moderated by the cosine-based factor. The variable K is a meeting coefficient, computed by scaling D with a constant k. The appearance $W(it)$ refers to the weight vector or explanation associated with the current gorilla, while $Wq(it)$ and $GXq(it)$ are solution vectors designated from the population. The term $W_{silverback}$ represents the best-performing solution (silverback) found so far. $G$is a guidance vector resulting from the scaled weight vector and range restriction Y, which is defined as a symmetrical interval$[-D, D]$. $N$is a standardization factor based on the mean of population situations, controlled by the exponent h, which is exponentially ascended using K. The term R is a random scaling factor, and B is a behavioral alteration coefficient influenced by β, a tunable stricture, and F, a binary switching function that chooses between M_1 and M_2 depending on a probabilistic condition using Equations (12-16).

$$GX(it+1) = K \times N \times (W(it) - W_{silverback}) + W(it) \tag{12}$$

$$N = \left(\left|\frac{1}{M}\sum_{j=1}^{M} GX_j(it)\right|\right)^{\frac{1}{h}} \quad , h = 2^K \tag{13}$$

$$GX(l) = W_{silverback} - (W_{silverback} \times R - W(it) \times R) \times B \tag{14}$$

$$R = 2 \times q_5 - 1, \qquad B = \beta \times F \tag{15}$$

$$F = \begin{cases} M_1 & rand \geq 0.5 \\ M_2 & rand < 0.5 \end{cases} \tag{16}$$

Pseudo code 1 presented the AGT-ARNN model to enhance metadata classification in digital libraries. By optimizing hyperparameters and focusing on relevant tokens in full-text documents, it improves accuracy, semantic relevance, and efficiency in information retrieval across complex digital library environments.

Pseudo code 1: AGT-ARNN model

Input: Initialize gorilla population with random ARNN parameters

Output: Set max_iterations, learning_rate_bounds, dropout_bounds, etc.

for iteration in range(max_iterations):

for each gorilla in the population:

accuracy = train_and_evaluate_ARNN(gorilla.parameters)

if accuracy > best_accuracy:

silverback = gorilla

best_accuracy = accuracy

For each gorilla in the population:

if random() < threshold:

gorilla.parameters = random_within_bounds()

Else:

direction = compute_direction (silverback, gorilla)

gorilla.parameters = update_position(gorilla.parameters, direction)

Train best ARNN with Silverback. parameters

for the document in test_documents:

tokens = tokenize_and_embed(document)

attention_scores = compute_attention(tokens)

metadata = classify_with_ARNN (tokens, attention_scores)

store(metadata)

IV. RESULTS

The experimental setup was conducted on a system equipped with an Intel Core i7 processor, 32GB RAM, and an NVIDIA RTX 3080 GPU. The model was implemented using Python with TensorFlow and Keras libraries on an Ubuntu 20.04 environment. The proposed AGT-ARNN model is compared against existing approaches, such as the Rule-Based method, Support Vector Machine (SVM), and Bi-directional LSTM, as presented by Safder and Hassan (2019), highlighting its superior capability in semantic metadata extraction, classification robustness, and retrieval effectiveness within digital library environments. To analyze an evaluation of the potential of the suggested method, this attempts to optimize metadata structures. This demonstrates an increase in semantic understanding and retrieval. The outcome of this activity supports the incorporation of DL and optimization approaches to advance digital library retrieval systems, using accurate metadata extraction.

Fig. 2 shows the performance of the AGT-ARNN model training and validation across 100 epochs. The training accuracy in Fig 2 (a) increased steadily to above 95%, while the validation accuracy fluctuated around 30–35%, showing some overfitting. Fig 2 (b) shows that training loss decreased consistently and validation loss increased, which confirmed overfitting. These results indicate that the model is learning from the training data, however, additional data or regularization needs to be addressed to perform well from the unseen.

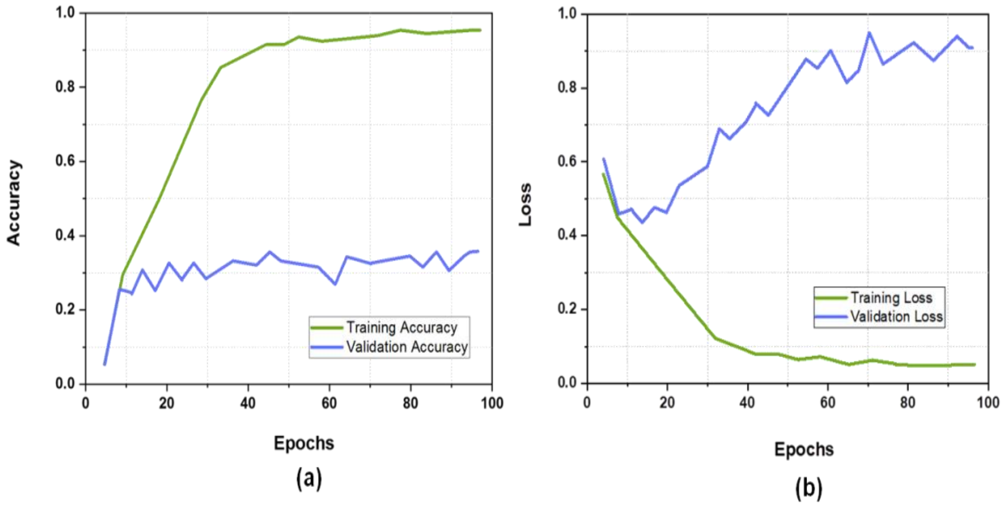

Fig. 2 AGT-ARNN Model Performance Across 100 Epochs, (a) Training and Validation Accuracy Curve, (b) Training and Validation Curve

Fig.3 represents the cosine similarity of different research topics using textual data and shows semantic relations. The strong cosine similarity between Semantic Metadata Extraction and Doc Classification Attention shows that attention-based deep learning is very highly relevant to successful metadata extraction; however, this is a central aim of the proposed AGT-ARNN models enhanced metadata structures. This visualization attests to the relative alignment of topics and highlights how semantically similar tasks can relate to constructing decisions when modeling such information for the search and retrieval of digital libraries.

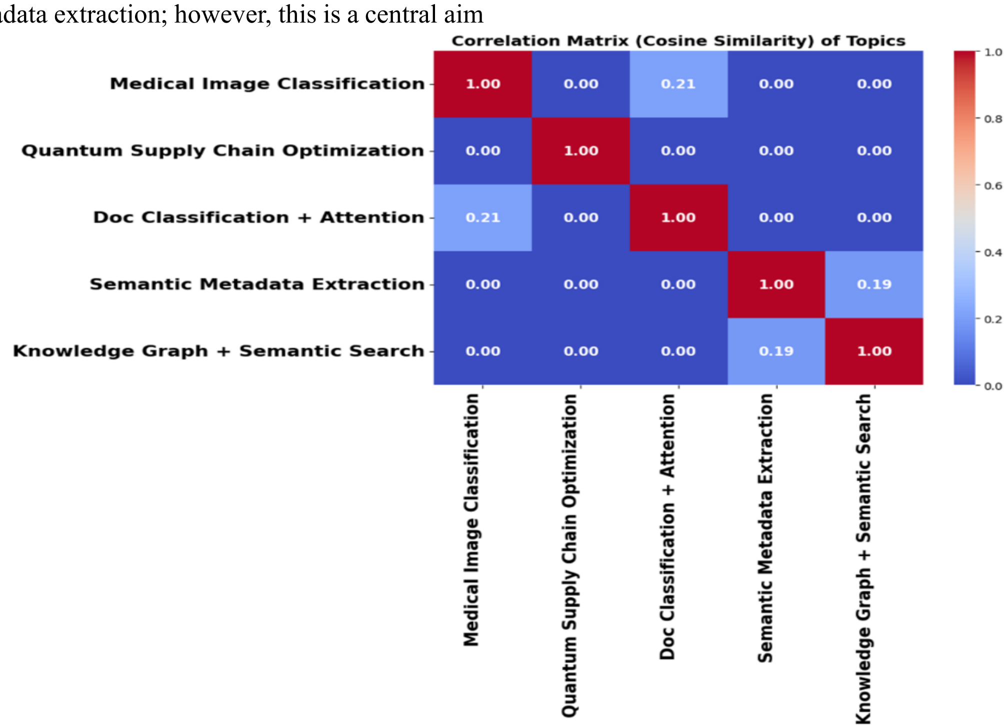

Fig. 3 Correlation Matrix

The performance evaluation contrasts different metadata categorization techniques, such as Rule-Based and Support Vector Machine (SVM) approaches by (Safder & Hassan, 2019), and a Bi-directional LSTM model, as shown in Table II and Fig. 4. With an accuracy of 50% and an F1-score of 14%, the Rule-Based approach performed poorly, whereas SVM demonstrated a moderate improvement. The Bi-directional LSTM performed better, achieving an 81% F1 score. In contrast, the suggested AGT-ARNN model beat all previous techniques, with 97% accuracy and a 95% F1 score.

This demonstrates the effectiveness of combining adaptive optimization with focus methods to improve semantic information extraction in digital library systems.

TABLE II COMPARISON OF CLASSIFICATION PERFORMANCE ACROSS METHODS

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Rule Based (Safder & Hassan, 2019)	50	15	20	14
SVM (Safder & Hassan, 2019)	74	75	74	74
Bi-directional LSTM (Safder & Hassan, 2019)	81	80	82	81
AGT-ARNN [Proposed]	**97**	**90**	**93**	**95**

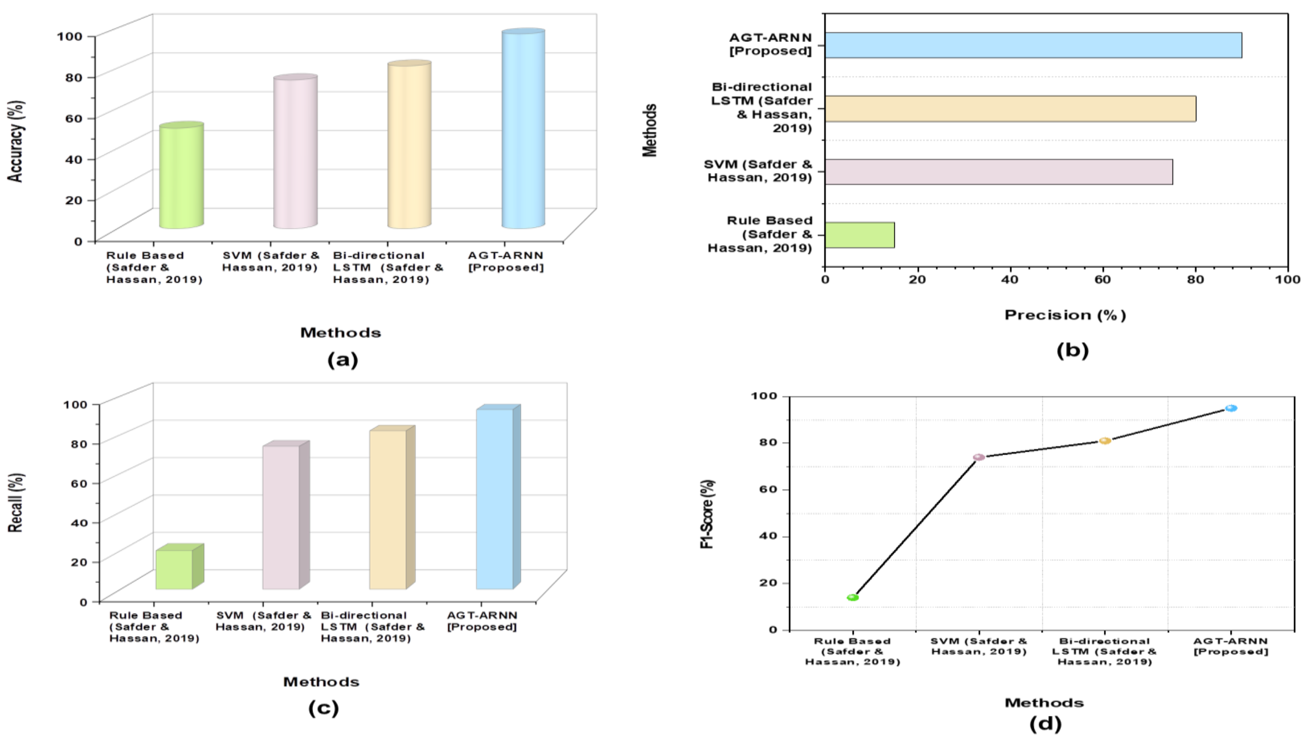

Fig. 4 Performance Comparison of Classification Methods Across Metrics

V. Discussion

The AGT-ARNN model is highly effective for semantic metadata classification for digital library applications. The experimental results show that the model achieves strong performance in classification, with 97% accuracy and a 95% F1 score. The performance significantly surpasses that of existing methods, including rule-based methods, SVM, and bi-directional LSTM (Safder & Hassan, 2019) models, showing uniqueness in combining adaptive optimization with attention-based deep learning. While the model exhibited high-learned behavior during training, the gap between the training and validation behavior implies over-fitting. This shows that either applying regularization strategies, or an increase to the number of documents included in the dataset, can result in improved generality. Similarly, the semantic similarity found between metadata categories, in addition, supports the importance of attention mechanisms to learn contextual dependencies that are valuable for extracting metadata accurately. Overall, these findings suggest the AGT-ARNN model is efficacious in improving information retrieval performance, as it can generate both semantically relevant and semantically useful metadata.

VI. Conclusion

DL is particularly well-suited for optimizing metadata structures and allows for improved effectiveness for searching and retrieving collections from digital libraries. It will learn about the AGT-ARNN model, which pairs attention mechanisms to the AGT Optimizer and produces key performance indicators, including accuracy of 97%, precision of 90%, recall of 93%, and F1-score of 95% better than keyword methods, such as rule based, or SVM. The proposed model improves search relevance and efficiency by producing semantically enriched metadata directly from full-text documents. Research findings have determined that the conjunction of adaptive optimization and deep learning models can be an effective approach to facilitate intelligible and intelligent metadata classification in digital library systems.

Limitation and Future Scope: The AGT-ARNN model shows remarkable performance; however; the computational complexity challenges in scaling to larger size digital libraries will be trade-offs for future research. Exploring minimizing model efforts, integrating multi-modal data sources, increasing real-time responsiveness, and recognizing units of observation will help generalize across multiple digital library practices and information retrieval systems.

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