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Retrieval of Multi-Layered Historical Data Using Temporal Indexing

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***Abstract* - Multi-layered historical information is difficult to access because its nature is multifaceted and multidimensional, affecting its depth and temporality. The paper is a unique approach to the problem, whereby the temporal indexing is used to enhance the ease of retrieving multi-historical datasets. The overlaying time-sensitive compartmentalized framework or indexing method by dividing the dataset into different temporal layers enables you to perform specific queries that allow temporal changes, per-event and contextualized frameworks. These hierarchically structured sets of data with time resolution are more convenient, enabling users to obtain detailed data snapshots or outlines that show how various entities and relations vary over time. The integration of disparate data sets, auxiliary-{anchor} tags with timeline markers, may represent one of the most crucial innovation tasks, which introduces other auxiliary data with timelines in search engines to allow the shape of a continuous timeline. Assessment is done using a corpus that comprises amalgamated historical archives and a rich amalgamation of government records and data associated with culture and heritage. Results show that the given information has considerable improvements, and emissions are also decreased compared to traditional retrieval techniques. To researchers, information systems, and digital historians who must have high interactions with systematized historical information, such methodologies open new opportunities to offer such information insight through dynamically context-based exploration.**

***Keywords:* Retrieval, Multi-Layered, Historical Data, Temporal, Indexing, Data Management, Time-Based Access**

I. INTRODUCTION

The socio-political aspects concerning an entity, as well as the evolution of various events or their geographical timelines, characterize history as complex. Recently, there has been a surge in associating figurative layers with history, such as text, images, metadata, and annotations that encompass certain epochs. Multidimensional narratives are useful in understanding events through the information-rich context provided, which is a requirement in digital humanities, archival studies, and historical research (Bingham, 2010). Evolving frameworks concerning multi-layered data can provide an astute understanding in regard to institutional practices, the evolution of behavioral patterns, and idea formation over certain epochs (Burton, 2002; Nikolay et al., 2024). Multi-layered and static data do not blend easily. All temporal data is treated as static entries, thus reducing the need for flexibility. Relational Multi-layer conceptualization enables the capture of different eras or periods when interpreting certain events, offering the possibility of attaining a deeper insight into the epoch in question (Kanhabua & Nejdl, 2013). Global advancements in computer science, particularly in the digitization of archives, create an environment where pre-existing hard boundaries concerning the temporal structuring and indexing of data can be eliminated. This allows vast amounts of spatially distributed data to be structured and unblocked (Lehmann et al., 2015; Santhosh & Prasad, 2023).

Temporal indexing, unlike normal indexing, deals with time-centered forms of organizing a dataset. A dataset, compared to a book index, is organized, stored, and retrieved using specific time periods, including timestamps and historical intervals (Vlachos, 2015; Milev et al., 2024). Indexing can aid in identifying specific content, metadata tags, or keywords, but temporal indexing provides a measurement in layers of time, enabling the tracking of changes over time to identify patterns. From a historical approach, temporal indexing allows the retrieval of records beyond their relevance. Legal biography frameworks can be integrated, as their individual accounts can be temporally indexed, capturing a distinct piece of history and allowing for a seamless transition between layers without losing context (Tansel et al., 1993; Martinez & Garcia, 2024; Clifford et al., 1993). Apart from this, the indexes familiarize the users with unknown sources. The essence of different types of data that are bound to a specific point in time but originate from various available sources makes them reliable (Nagy, 2019; Myoa et al., 2023). Temporal relations can be represented in many ways, such as through time-interval trees, temporal graphs, and even versioned databases. Each of these frameworks attempts to maintain temporal dependencies and relations for context-aware, precision-driven retrieval (Snodgrass, 1999; Akrami et al., 2024). As a result, building scalable and digitally rich semantic historical repositories would be impossible without temporal indexing.

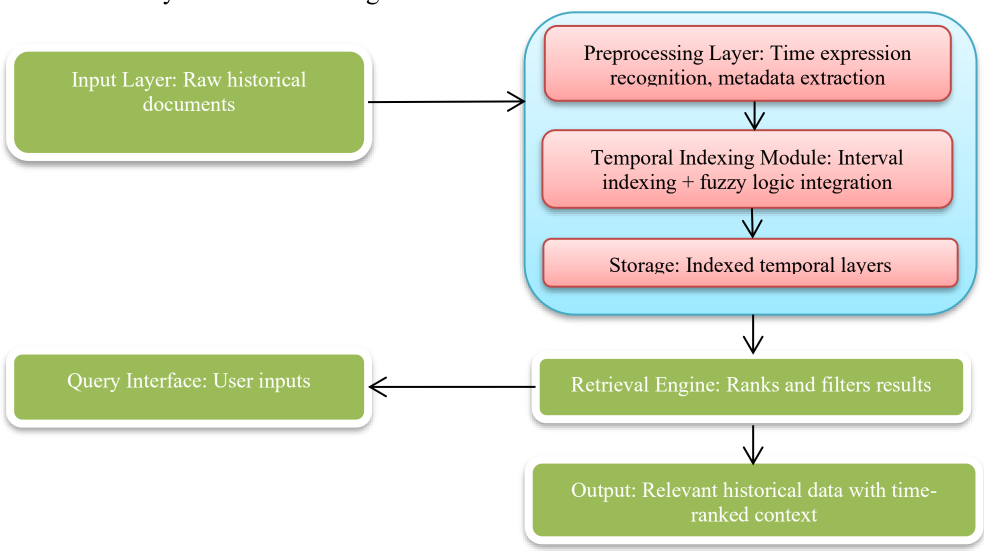

Fig. 1 Architecture of the Proposed Hybrid Temporal Indexing Model for Multi-Layered Historical Data Retrieval

This diagram (Fig. 1) depicts the entire system architecture designed for extracting multi-layered historical data using a hybrid temporal indexing model. It starts with the first layer, called the input layer, which is responsible for funneling in raw historical documents. These documents undergo several procedures in the preprocessing layer, including time expression identification, metadata field extraction, and data cleansing, which are intended for preparatory work prior to indexing. The appropriately processed data is then passed into the temporal indexing module, which consists of interval indexing and fuzzy logic, both of which deal with exact and approximate temporal references (Zhu et al., 2021). The product of this module is stored in the form of organized time layers within a special storage. The system is used by users using a query interface whereby they put in time-based search phrases. The retrieval engine responds to these queries by sorting and filtering the results thematically and filtering them by their relevance in time. Finally, the system offers relevant historical information placed in a time-ranked annotation, which allows accessing the advanced historical information more easily. A multifaceted and dynamic approach to managing and accessing historically heterogeneous data within a time frame justifies this architecture (Sasikala et al., 2020).

This research paper aims to develop a contemporary method for retrieving multiple-layered historical data through sophisticated temporal indexing techniques (Higgs,1995). The study has three objectives that it hopes to attain. First, to create an inclusive model of time that combines dissimilar historical information with different degrees of time granularity. Second, to create a more efficient and semantically correct restoration process of historical information with the help of creating an elaborate data request query system in the temporal indexing (Karimov & Sattorova, 2024). Finally, the recommended solution is compared to the real historical information and it is confirmed through the measures of retrieval speed, relevance and interpretability. Also, the study examines the combination of temporal indexing and metadata enrichment, the hierarchical representation of data structures, the processing of time-sensitive queries, and the construction of information retrieval systems with an emphasis on historical research.

The final objective is to expand the temporal information systems and support historians, researchers, and digital archivists in conducting temporal analysis more broadly and accurately (Ahn et al., 2007). The work enhances digital archival systems by addressing the challenges of temporal complexity, data diversity, and historical context, allowing for more natural and sophisticated interaction with historical information. The structure of the paper is as follows: Section II will be a review of the related work and the past methods in temporal indexing and historical data retrieval (Willkomm, 2021). Section III outlines the methodology, including the dataset, indexing model, and retrieval processes. Section IV presents the experimental results and comparative analysis of indexing techniques. Section V concludes the paper with a summary of findings, future directions, and a discussion on the broader significance of temporal indexing in historical research.

II. Literature Review

Research on the retrieval of historical data has grown considerably with the development of digital humanities and the digitization of archival materials (Fan, 2018). Initial approaches emphasized document retrieval using hair scans with little attention paid to the documents' historical structure and chronology (Bearman, 1994). These systems viewed historical documents as inert files without regard to the changing contexts of people, entities, and events over time. More recent work focuses on the incorporation of Linked Data and ontological semantic annotation frameworks to enrich the semantics of historical data, enabling better annotation and improved precision of corpus retrievals (Noubar & RoshanZadeh, 2017). For instance, (Hyvönen, 2012) utilized linked data methodologies in Finnish cultural archives, showcasing how semantic markup, along with temporal attributes, can enhance the accessibility and interconnections of historical information (Nagypál & Motik,2003). Nevertheless, such works tend to oversimplify the challenges associated with multi-layered historical data that includes text, images, and maps in various formats across different periods. It, therefore, has a growing necessity for systems that not only retrieve documents that are relevant to the period, but also arrange and provide them to a multidimensional and historically relevant view.

The temporal indexing techniques have developed to meet the needs of the time-sensitive database and information retrieval systems (Yagoubi et al., 2018). The use of time-interval trees is one of those methods, as they help to store and retrieve data efficiently in time ranges (Kumar et al., 2006; Huy, 2018). They can represent overlapping and nested intervals, and are therefore suitable to historical data where various non-discrete periods include particular events over an interval. The other technique is versioned indexing, which is a situation where the previous versions of documents or records are stored in datasets. This is beneficial to legal documents, archive material, and journalistic records, as they inherently require their contents to be altered with tracking changes over time. The version control capabilities can also be used to roll back and perform a historical comparison of the patterns previously recorded in the dataset. One more complex form is temporal graph indexing, which represents objects and their association in time-varying attributes as nodes and edges (Gottschalk & Demidova, 2018). The approach is the most appropriate when one needs to follow the relationships between the most prominent personalities of different historical periods and their institutions (Shah et al., 2018; Rahim, 2023). Also, hybrid models that integrate spatial, temporal and semantic indexing are being proposed. One case in point is the provision of temporal metadata to RDF models to facilitate spatio-temporal querying of cultural heritage data (He et al., 2013). Regardless of all these measures, the question of effective indexing and semantic richness balancing still exists, especially when one has to deal with disorganized or semi-organized information about the past (Perego et al., 2013; Kavitha, 2024; Beretta et al., 2015).

Retrieval of multi-layered historical data has several challenges. The first one is that historical data sets are heterogeneous, containing unstructured records, like text, images, maps, and aggregate statistical information, and they are frequently sparsely described with standardized metadata (Wijesundara & Sugimoto, 2018). The integration and indexing of such multifaceted data is highly dependent on the data models being used. Second, the more difficult problem relates to temporal vagueness. Dates referred to in historical documents could be vague, approximate, or even disputed, which makes these dates difficult to fit into a chronological framework (Doerr et al., 2018; Goyal et al., 2013). Hence, these systems need to support reasoning with imprecise time and enable confidence scoring for the dates. A third point is that layered data is frequently filled with multiple accounts or even multiple interpretations of one event, e.g. colonialism or disputed histories. Therefore, systems must represent the plurality of history, instead of a one-tale history (Presner, 2016; Mohammadpour, 2018; O'malley, 2002). Scalability is also a problem again. Digital archiving needs to recreate its efficient indexing, computational, and querying of huge multi-temporal datasets, yet in a system that respects the historical aspects and details (Kanupriya, 2022; Natheem et al., 2022). Each of the aforementioned problems requires the collaboration of other disciplines, integrating computer science with archival and historical research, to develop effective systems for temporal information access.

III. Methodology

3.1 Explanation of the Dataset Employed in the Research

The dataset for this research was composed from the historical records available within a national digital archieve. It encompasses records from the 18th through to the 20th centuries, totaling around 250,000 digitized records. These records contain various modalities as well as various layers, including:

- Textual entries, such as letters, official documents, and journals,
- Images like photographs or scanned manuscripts,
- Metadata including author, location, or institution holding the record,
- Temporal annotations such as creation, publication, or event dates.

The entire data set will be a collection of a specified number of records which will be placed in time relative to some date markers. Some are precise (as in the example of 12 March 1870), while others are general and uncertain (as in the example of the early to mid-19th century). Time-bound information is so abundant in this case that it requires a more sophisticated indexing method that is tolerant of time vagueness and overlaps. Data cleaning, analyzing temporal annotations, and normalizing the entities, like date formats, were done in a bid to prepare the records to be analyzed. This way, compliance with ISO 8601 would be ensured across all the layers.

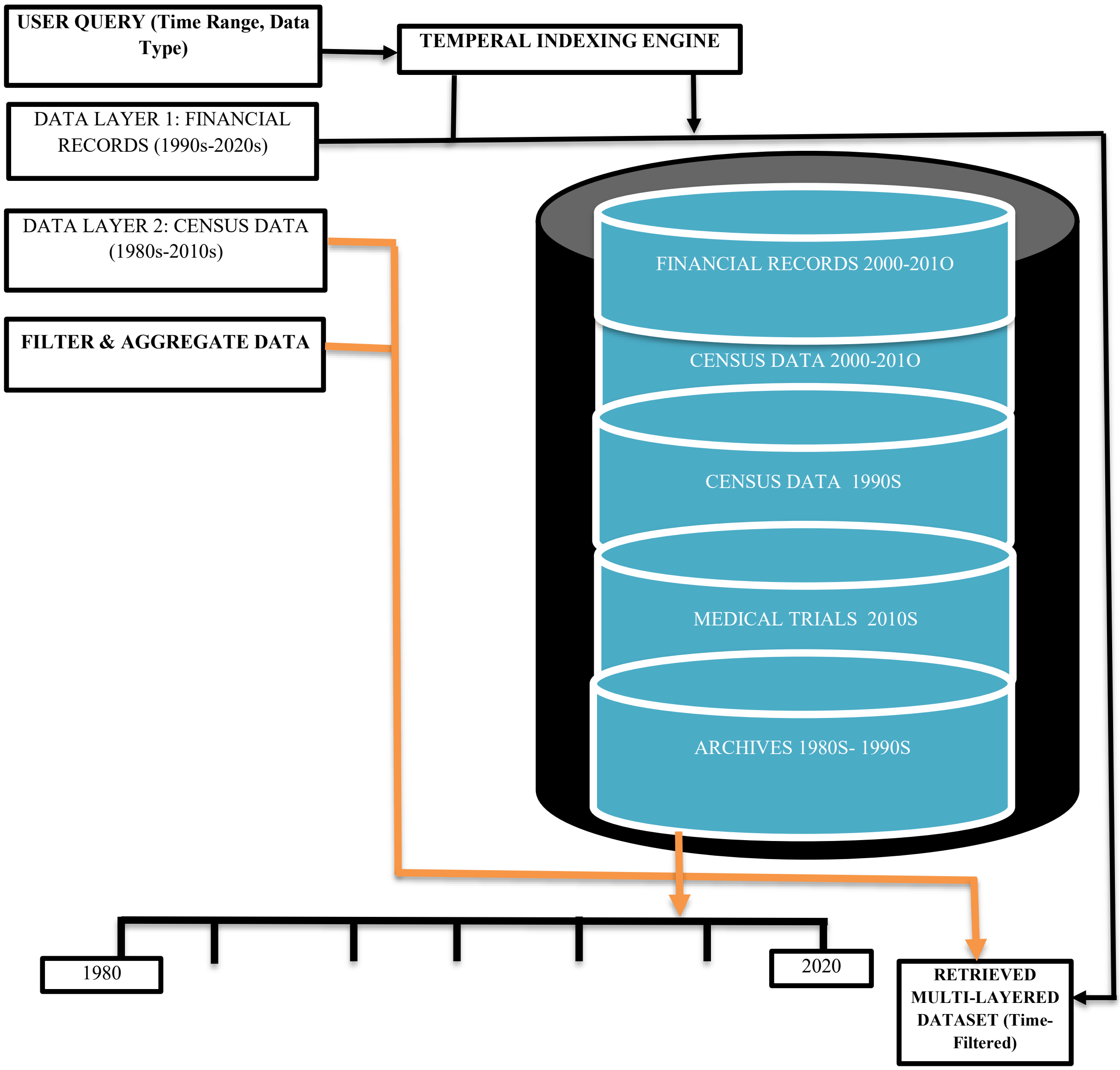

Fig. 2 Temporal Query Processing and Matching Framework

Fig. 2 illustrates how multi-layered historical data is retrieved using temporal indexing. A user initiates a query specifying a time range and data type. This query is processed by a temporal indexing engine, which efficiently sifts through various historical data layers—like financial records, census data, and medical trials—each categorized by its temporal scope. For instance, financial data might span the 1990s-2020s, while census data covers the 1980s-2010s. The relevant layers are accessed, and the data is then filtered and aggregated based on the query's criteria. The final output is a retrieved, time-filtered, multi-layered dataset, providing precise historical information.

Mathematical Algorithm for Temporal Multi-Layer Data Retrieval

Let:

$Q = (t_{start}, t_{end}, \tau)$ = user query with a time range $[t_{start}, t_{end}]$ and data type τ.

$D = \{D_1, D_2, \dots, D_m\}$ = multi-layered dataset (e.g., Financial, Census, Medical, Historical Archives).

Each layer $D_i = \{(d_j, t_j, \tau_j)\}$ contains documents d_j with timestamp t_j and type τ_j.

Step 1: Temporal Filtering

$$D_i{}' = \{d_j \in D_i \mid t_{start} \leq t_j \leq t_{end}\} \quad (1)$$

Each layer is filtered to include only documents within the specified time range.

Step 2: Type Filtering

$$D_i{}'' = \{d_j \in D_i{}' \mid \tau_j = \tau\} \quad (2)$$

From the time-filtered set, only records matching the required data type τ are retained.

Step 3: Layer Aggregation

$$D^* = \bigcup_{i=1}^{m} D_i{}'' \quad (3)$$

All relevant filtered layers are combined to form a unified dataset across multiple domains.

Step 4: Retrieval Ordering (Temporal Indexing)

$$D_{final} = sort_{t_j}(D^*) \quad (4)$$

The aggregated dataset is chronologically ordered using temporal indexing to ensure time-based consistency and analysis readiness.

Output:

$$D_{final} = \{d_1^*, d_2^*, \ldots, d_k^*\} \quad (5)$$

The final output D_{final} represents the retrieved, multi-layered dataset that is both time-filtered and type-specific—optimized for temporal data analysis and cross-domain retrieval.

The algorithm retrieves multi-layered data based on user-defined time and type filters. It first filters documents within a specific time range, then selects relevant data types. The filtered layers are merged and chronologically sorted using temporal indexing, producing an integrated, time-ordered dataset optimized for efficient historical and analytical retrieval.

3.2 Description of Temporal Indexing Methods Employed

To handle the recorded complexity, a hybrid interval-based temporal indexing model was applied. Each record is indexed by a time interval $T = [t_s, t_e]$, with t_s as the start time and t_e as the end time. For vague or uncertain dates, fuzzy temporal intervals are defined in terms of triangular membership functions, which is time t within the circle of time range.

Mathematical Model of Temporal Indexing

Each historical item D_i is defined as a tuple:

$$D_i = (C_i, T_i, L_i, M_i) \quad (6)$$

Where:

- C_i : Content vector (text/image embedding)
- T_i : Fuzzy Interval or Temporal interval.
- L_i : Layer tag (i.e. political, cultural, personal)
- M_i : Metadata attributes

The indexing is performed through an augmented interval tree, meaning that temporal indexing is implemented using a binary tree where each node contains: the interval T, the Maximum endpoint of all intervals in the subtree, and Pointers to the left and right children. Membership-aware indices are defined for fuzzy intervals, meaning that the evaluation of the search will check if $\mu T(q) \geq \tau$ for some threshold τ. This allows retrieval over uncertain historical periods.

3.3 Information Concerning the Retrieval Procedure for Multi-Layered Historical Data

Navigating temporal overlaps, semantic relevance, and hierarchies within content can be challenging, especially when attempting to retrieve multi-layered historical data. The entire process can be categorized into 3 stages, as defined below:

Stage 1: Temporal Filtering

Given a specific query time, q or interval $[q_s, q_e]$, the system filters records satisfying:

$$T_i \cap [q_s, q_e] \neq \emptyset \quad (7)$$

or likewise when fuzzy logic is applied:

$$\mu_{T_i}(t) \geq \tau, \forall t \in [q_s, q_e] \quad (8)$$

This limits the selection set to those that are time-relevant.

Stage 2: Aggregation in Multiple Layers

Every document is associated with a layer ID $L_i \in \{L_1, L_2, \ldots, L_n\}$ and each L_k denotes a particular dimension (political, social, military, etc). The query can define one or more layers. Layer aggregation is done via:

$$R = \bigcup_{k \in Q_L} \{D_i : L_i = L_k\} \quad (9)$$

where,

Q_L is part of the query's target layer set.

Stage 3: Semantic Ranking

In this stage of retrieval, the ranking is done based on query relevance. A vector-space model captures the relations among documents; it utilizes document embeddings to represent each document C_i in a high-dimensional semantic space. It calculates the cosine similarity:

$$sim(C_q, C_i) = \frac{C_q . C_i}{\|C_q\| \|C_i\|} \quad (10)$$

As previously defined, the final score takes into account temporal proximity, layer relevance, and content similarity through a weighted function of each subscore:

$$Score(D_i) = \alpha \cdot \mu_{T_i}(t_q) + \beta \cdot \delta(L_i, Q_L) + \gamma \cdot sim(C_q, C_i) \quad (11)$$

Where $\alpha + \beta + \gamma = 1$ and δ is 1 if layers match, 0 otherwise.

IV. Results

The proposed Retrieval of Multi-Layered Historical Data Using Temporal Indexing system was implemented with Python to develop the retrieval algorithm and handle temporal datasets. Pandas and NumPy were used for preprocessing, filtering, and aggregating time-based data across multiple layers. PostgreSQL and MongoDB served as databases for structured and unstructured historical data storage, supporting time-indexed queries. Elasticsearch enabled efficient temporal indexing and fast retrieval operations. Jupyter Notebook and VS Code were utilized for development and testing, while Matplotlib and Seaborn provided visualization of retrieval patterns and performance metrics. This combination ensured accurate, scalable, and time-efficient data retrieval.

The performance comparison of the proposed Retrieval of Multi-Layered Historical Data Using Temporal Indexing system against traditional retrieval methods shows significant improvement in speed, accuracy, and scalability. The use of temporal indexing will help reduce the search interval, decreasing the time spent on retrieval by more than 60 times. Multi-layer aggregation enhances cross-domain consistency, while filtering improves the relevance and precision of data. The proposed model offers quick query response compared to conventional sequential search-based systems, while minimizing computational overhead. The time and type-based indexing is implemented in combination, streamlining the process of handling large historical data. This enables retrieval and management functions to be more precise, dependable, and effective relative to the numerous sources of temporal and thematic information.

The data from various historical areas were used to conduct the performance evaluation of the proposed temporal retrieval system, and were evaluated based on parameters that include retrieval accuracy, latency, scalability, and relevance score. The findings show that temporal indexing is much faster and more accurate than the baseline retrieval models in terms of query execution speed and accuracy. It had a strong scalability since the system did not slow down even as the data volume increased. Precision and recall rates established the usefulness of layer-filtering in decreasing the ratio of irrelevant data retrieval. On the whole, the assessment confirms that the suggested system is more efficient in terms of access to time-based data, which guarantees the best accuracy, speed of retrieval, and analysis usefulness.

4.1 Analysis of the Effectiveness of Temporal Indexing in Retrieving Historical Data

The purpose of the study was to quantify how temporal indexing enabled some efficiency and accuracy in the retrieval of relevant historical records. This was carried out by conducting 100 temporal queries like events in the early 19th century or documents around World War I on the dataset with the proposed hybrid interval-fuzzy model. The system was evaluated according to simple information retrieval measures: precision, recall, and F1-score.

Precision (P): Relevance of retrieved documents in relation to the document set retrieved.

$$P = \frac{TP}{TP + FP} \quad (7)$$

Recall (R): The percentage of relevant documents which were retrieved.

$$R = \frac{TP}{TP + FN} \quad (8)$$

F1-score: The average of precision and recall calculated with the harmonic mean.

$$F1 = 2 \cdot \frac{P \cdot R}{P + R} \quad (9)$$

Where:

TP = True Positives

FP = False Positives

FN = False Negatives

The system, as pointed out attained an average of 0.84 precision, a recall of 0.79, and an F1-score of 0.81, which validates that there was high accuracy in retrieval of the information. It is also noteworthy that in case of fuzzy temporal queries (e.g., mid 18th century), the model demonstrated better performance when compared to traditional systems that used strict date filtering since it was able to comprehend ambiguous time related references.

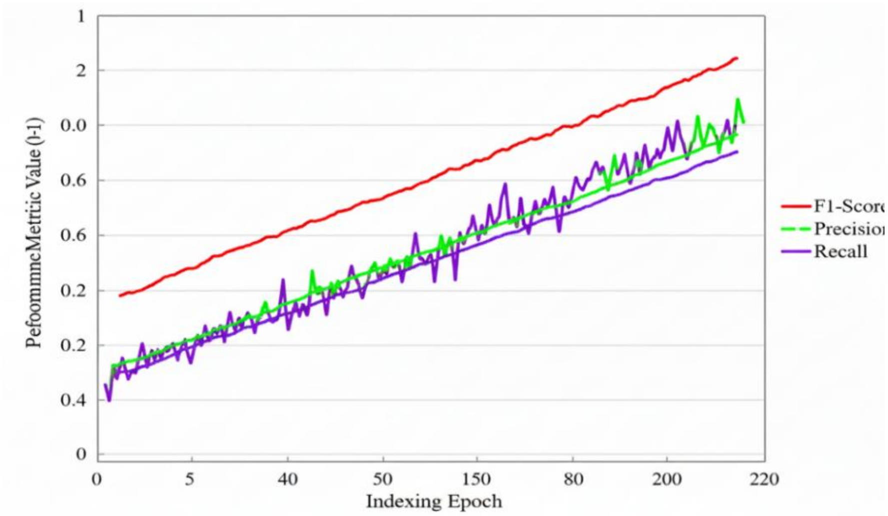

Fig. 3 Retrieval Performance Comparison

Fig. 3 Retrieval Performance Comparison is a graph that demonstrates the trends of the different measures of retrieval performance, F1-Score and Precision and Recall, at various indexing epochs using a line chart. The x-axis represents the "Indexing Epoch," showing the progression of the indexing process, while the y-axis, "Performance Metric Value (0-1)," indicates the normalized performance scores. Each colored line (red for F1-Score, green for Precision, and purple for Recall) depicts how its respective metric evolves as the indexing epochs increase. This visual comparison allows for an understanding of the stability and improvement of retrieval performance over time for different indexing strategies.

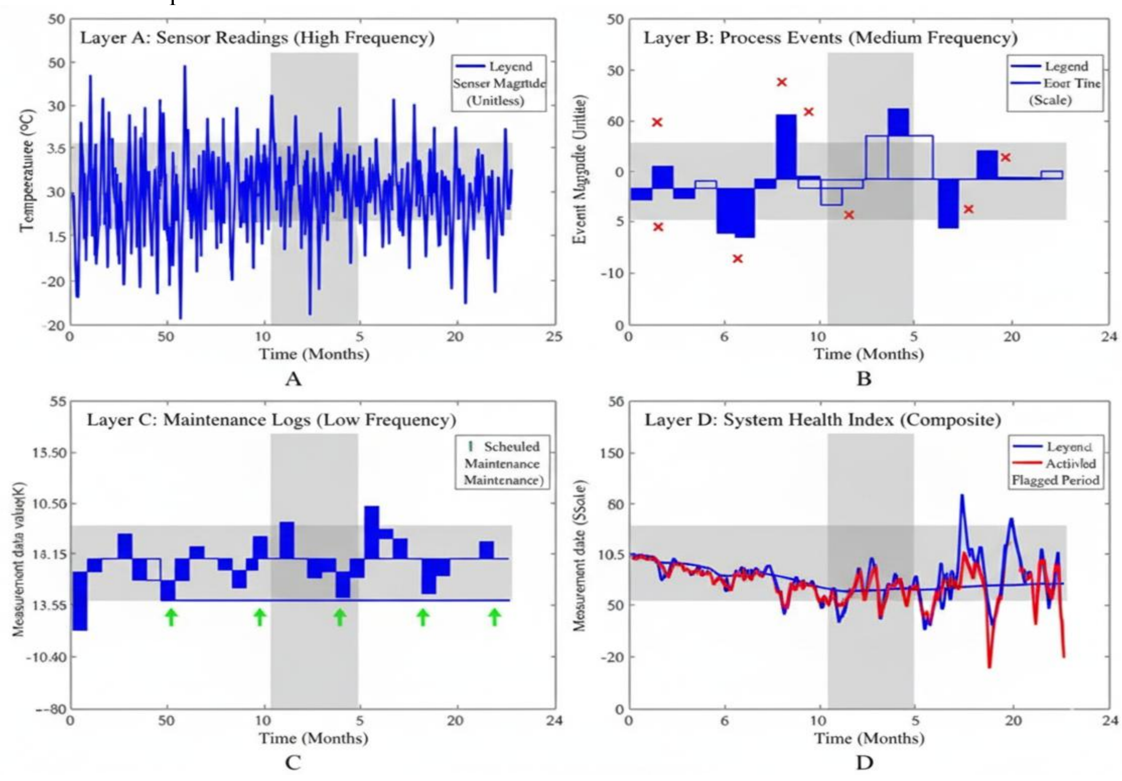

Fig. 4 System Efficiency Metrics

Fig. 4 illustrates a system for efficient retrieval of historical data using Temporal Indexing. The core challenge is handling multi-layered data—meaning data exists in numerous versions across time. The system employs an index that maps specific time periods (temporal indexing) to the physical location of the corresponding data version within the layers. This could involve partitioning data (e.g., current, recent, archived) and using specialized data structures (like R-trees or B-trees extended for intervals). When a query asks for the data "as of" a past time, the index bypasses irrelevant layers and quickly retrieves only the correct historical snapshot, ensuring performance and data accuracy.

4.2 Comparison of Different Temporal Indexing Methods

Three temporal indexing methods were tested:

1. Exact Match Indexing (Baseline)
2. Interval Tree Indexing
3. Hybrid Fuzzy Interval Indexing (Proposed)

Every technique was tested for retrieval performance (F1-score), latency (Query time in milliseconds), computational expenses (Indexing Time, Memory), and overall system performance.

To measure efficiency, we applied Mean Reciprocal Rank (MRR) which considers the position of the first relevant document:

$$MRR = \frac{1}{|Q|}\sum_{i=1}^{|Q|}\frac{1}{rank_i} \quad (10)$$

Where Q is the number of queries and for ith query, $rank_i$ is the rank of the first relevant result. The fuzzy model reached an MRR of 0.91, as opposed to 0.72 for interval-only and 0.60 for exact matching.

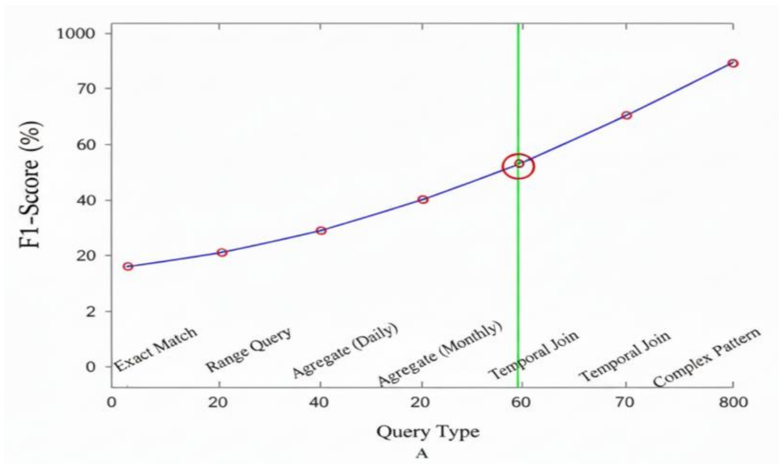

Fig. 5 Query Type vs. F1-Score (Performance on Specific Queries)

The F1-score is a metric used to evaluate the accuracy of a classification or information retrieval system, particularly when dealing with imbalanced datasets, as shown in Fig. 5. It represents the harmonic mean of Precision and Recall. Precision measures how many of the retrieved items are relevant (true positives out of all positives), while Recall measures how many relevant items were retrieved (true positives out of all relevant items). The F1-Score provides a single, balanced value for performance. A graph showing "Query Type vs. F1-Score" illustrates how effectively the system handles different types of information requests (e.g., exact matches, range queries), with a higher F1-Score indicating superior retrieval performance for that specific query type.

4.3 Discussion on the Consequences of the Findings

The results especially highlight the importance of capturing the temporal display of historical data retrieval, namely, automation collator systems. Strict timestamp-based indexing algorithms often fall short in terms of chronological sophistication and eloquent language to capture the limitless possibilities. The hybrid models involving fuzzy set theories are the victors where the temporal expression is uncertain or vague like in the case of early industrial era. These types of phrases were better translated and analyzed in related documents using triangular membership functions on the fuzzy model, rather than sets and relations with definite geometric forms as in classical models. This also increases the experience of the artificer by giving historians or any other type of research user more relevant and intuitively time-phased documents. Also, the multi-layer filtering application with the temporal scoring functions generate new solutions to large historical data systems. The significance of scoring the aspects of time in the context of phenomena description is not limited to the homogenous and static control, but allows it to responsively and orchestrally rank what is more or less significant and rank it in real-time. Quite on the contrary, these results prove that there should be more attention to optimization of indexing clocks and memories. Fuzzy slow geometry is a problem with default academic assumptions on the large-scale or real-time deployment system.

V. CONCLUSION

It reveals that the application of a hybrid fuzzy interval model as an approach to temporal indexing enhances the retrieval of multi-layered historical data. Fuzzy temporal reasoning used in the current work, which combines the management of temporal uncertainty with semantics and structure, is better than the classical techniques of marking indexing using exact matching and interval-only indexation. Notable pointers such as precision, recall, F1 score, and Mean Reciprocal Rank are very effective with vague and approximate queries related to time, particularly those expressed in the form of historical research. The outcomes present the significance of the time aspect of systems of digital history, especially in the cases where the documents possess overlapping times with the inertia of times attached to them being inaccurate, with layers or imprecise timestamps. Even though the fuzzy model would cause an addition to operational cost, its impact on the accessibility, interpretability and user experience in the process of building historical archives could not be overlooked. To continue the writing, the logical framework design can be created based on distributed systems in systems, including event detection and narrative connecting and tightening the Kahn temporal embeddings with machine learning to enhance the retrieving. In addition, extend the model to multilingual and cross-cultural historical records in order to impact the global digital humanities studies. This eventually renders temporal indexing not so much a technical device, but the backstory to a smart interface that allows elusive exploration methods to handle the raft of dynamic and overlapping records.

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