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NeuroNimbus: A Cloud-Powered AI System for Memory Reconstruction

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ABSTRACT

NeuroNimbus is an intelligent cloud-assisted system designed to help individuals with cognitive impairments perform digital memory reconstruction. Memory disorders make it difficult for individuals to remember people and events; as a result, they are forced to rely on caregivers and manual memory aids. To address these issues, the proposed system uses dual interfaces for caregivers and patients. Users upload images with accompanying captions through a web portal. Natural Language Processing (NLP) is used to analyse the uploaded captions to extract contextual keywords. TF-IDF is used to represent features and perform cosine similarity analysis to ensure consistency of memories stored by detecting redundant memories. Memories are organised into person and event categories based on assigned labels. NeuroNimbus provides an organised digital memory support system by integrating semantic processing, redundancy control, and security mechanisms with role-based access control. Experimental validation demonstrated an overall functional accuracy of 90.2%, indicating stable and reliable system performance in structured memory reconstruction tasks.

Keywords: Digital Memory Reconstruction, Natural Language Processing (NLP), TF-IDF, Cognitive Support Systems, Cloud Computing, Role-Based Access, Memory Organisation, Duplicate Detection, Healthcare Informatics

1. Introduction

Memory is an important aspect of human life. It enables a person to remember past experiences, identify known people, and preserve personal identity. However, certain neurological disorders, such as Alzheimer's and dementia, significantly impair a person's ability to remember events, people, and everyday details [4], [15]. As the disease advances, people find it difficult to remember significant memories and become more reliant on others for help. Although tremendous progress has been made across fields such as communication, healthcare, and education, memory-aiding technologies for cognitively impaired individuals still rely heavily on manual methods, such as notebooks, printed photo albums, and oral instructions. These traditional methods become cumbersome for both patients and caregivers. Individuals with memory impairment also face challenges, including a lack of digital literacy, the complexity of memory interfaces, and the need for caregivers to manage personal data [4]. Moreover, many existing digital memory storage systems lack intelligent organisation. Pictures and descriptions are often unorganised, leading to repeated entries, ambiguous descriptions, and the inability to retrieve significant information. Without automated keyword identification, similarity analysis, and contextual grouping, memory storage becomes disorganised and mentally taxing rather than supportive [5], [6]. To address these problems, this paper presents NeuroNimbus: A Cloud-Powered AI System for Memory Reconstruction, a web-based application that leverages Natural Language Processing (NLP) and cloud computing resources [13]. The application allows users to upload images and corresponding descriptive text. The text is then processed using NLP tasks to extract relevant keywords and information, making it easier to organise and structure memories into person-related and event-related groups based on assigned labels and contextual metadata. This makes it easier to organise and manage memories without requiring in-depth technical knowledge. Simple approaches such as TF-IDF Keyword Extraction and Cosine Similarity are used to automatically detect repeated or similar memory entries, ensuring that the memory database is

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well-organised and free from redundancy [1], [13]. The application also incorporates secure cloud storage with role-based access control, features separate interfaces for patients and caregivers, and ensures synchronised, scalable data management [13]. Existing memory support applications are generally limited to manual recording or to individual functionality, without intelligent automation or understanding [8],[18]. Most applications lack the capability for semantic processing and do not support automatic memory categorisation and redundancy management, making them less efficient for organised healthcare management. By integrating NLP-based contextual analysis with secure cloud services, NeuroNimbus provides a user-friendly, scalable solution for digital memory management. The system focuses on usability, lightweight processing, and organised storage, making it ideal for a healthcare setting where computational power and technical know-how might be constrained.

The main contributions of this paper are as follows:

(i) A cloud-supported system for structured digital memory reconstruction;

(ii) A keyword extraction and similarity-based categorisation system using NLP for grouping memories into significant categories;

(iii) A redundancy detection system for maintaining lightweight repository consistency;

(iv) A dual-interface and role-based system design to minimise cognitive overload for patients as well as caregivers.

2. Research Methodology

The framework is intended to convert unstructured image caption data into a well-organised, searchable memory bank using lightweight Natural Language Processing and secure cloud hosting. Unlike conventional human-operated memory storage solutions, the proposed framework integrates semantic analysis, redundancy management, and role-based access control as per Figure 1.

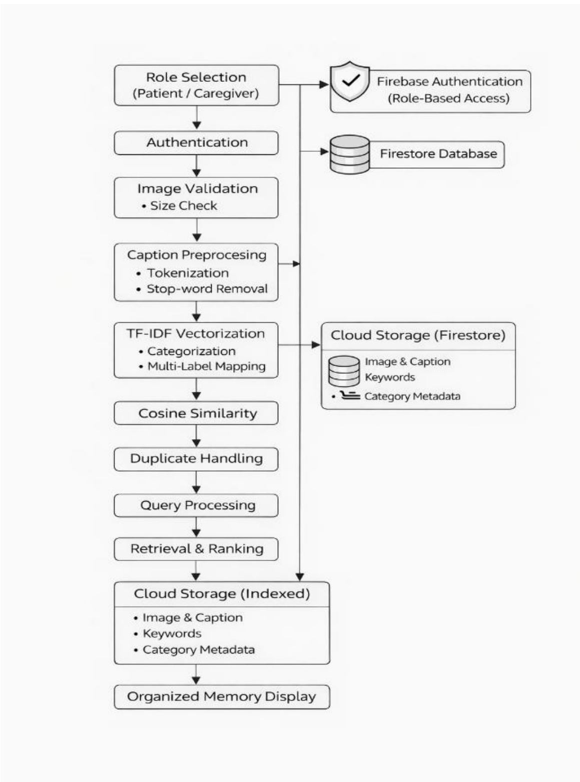

Figure 1. Architecture of the proposed NeuroNimbus framework.

NeuroNimbus uses a two-role architecture that includes a caregiver interface and a patient interface. The caregiver is tasked with creating and managing memory repositories. When patients register in the system, they are assigned a unique identifier to prevent duplicate data. The system has uniqueness constraints on patient names and identifiers to ensure structured storage and prevent overlapping entries. The patient interface provides controlled access to view categorised memories, special events, and caregiver-uploaded notes. Authentication is performed via cloud-based role validation to ensure that each patient can access only their memory repository. The process of memory reconstruction is initiated when a caregiver uploads an image with a caption and a corresponding person label. The system also allows additional contextual information, such as reminders or special event details (e.g., date and title). To ensure content is clear and consistent, the system uses validation constraints, including minimum image size requirements to prevent poor-quality images. Every memory entry is associated with a specific patient repository using the unique identifier generated during registration.

The uploaded memories are then submitted to the preprocessing and analysis stage. Each caption is normalised to eliminate linguistic noise and facilitate semantic extraction. The preprocessing step involves lowercasing, tokenisation, and stop-word removal. This processing step is necessary to prepare the text content for feature extraction while retaining significant contextual terms. The processed memory components, such as images, captions, extracted keywords, and category information, are stored in the cloud infrastructure. The cloud layer supports scalable storage, real-time synchronisation, role-based authentication, and logical separation of patient repositories. The cloud-based architecture supports horizontal scalability by separating authentication, storage, and indexing services. As the number of memory entries increases, indexing mechanisms ensure that retrieval performance remains efficient. Logical separation of patient repositories ensures stable concurrent access without data interference. The patient repositories are indexed using the unique identifier assigned during registration for secure storage. The search and retrieval mechanism supports keyword search, person grouping, and event filtering. When a search query is entered, the system searches the TF-IDF vectors and corresponding metadata for matching query keywords to retrieve the relevant memories. The result is shown in an organised memory display with images, captions, context tags, and categorised groups. The organised search and retrieval system is more accessible and user-friendly for people with memory disorders.

3. Theory and Calculation

To represent textual information numerically, TF-IDF vectorisation is applied. TF-IDF vectorisation and cosine similarity measures commonly used in NLP-based information retrieval systems were adopted in the proposed framework. The extracted keywords are used to improve contextual organisation and retrieval within the repository. Memories in the proposed system are organised into person-centred and event-centred groups based on labels and associated metadata supplied during memory upload.

For person-centred memories, the system groups memories based on the caregiver-assigned individual label, facilitating structured access within the People section. Event-centred memories are organised by event metadata, such as event name and date, facilitating retrieval within dedicated event categories. If similar images are uploaded with different contextual labels, the system retains a single image instance and maps multiple labels to it. This multi-association mapping helps in avoiding redundancy while maintaining semantic associations. This similarity-driven redundancy control ensures efficient cloud utilisation and prevents repository clutter.

The search and retrieval mechanism supports keyword search, person grouping, and event filtering. When a search query is entered, the system searches the TF-IDF vectors and corresponding metadata for matching query keywords to retrieve the relevant memories. The result is shown in an organised memory display with images, captions, context tags, and categorised groups. The organised search and retrieval system is more accessible and user-friendly for people with memory disorders. Although transformer-based deep learning architectures yield more complex contextual embeddings, they demand large amounts of labelled data and heavy computational resources. However, the proposed TF-IDF-based approach provides an interpretable, efficient semantic representation with lower complexity and faster processing time. This makes the approach feasible for implementation in a healthcare setting with limited infrastructure.

3.1. Mathematical Expressions and Symbols

The proposed NeuroNimbus framework employs mathematical formulations for memory representation, TF-IDF feature extraction, memory categorisation, similarity detection, search and retrieval, and computational complexity analysis. The equations presented below describe the mathematical foundation of the proposed system.

The memory dataset can be represented as:

$$M = \{(I_i, C_i)\}_{\{i=1\}}^{\{N\}}$$

where,

I_i represents the uploaded image,

C_i represents the corresponding caption,

N represents the total number of memory entries.

The term frequency (TF) of a term t in caption Ci is defined as:

$$TF(t, C_i) = \backslash frac\{f(t, C_i)\}\{\Sigma f(k, C_i)\}$$

The inverse document frequency (IDF) is given by:

$$IDF(t) = \log\left(\frac{N}{df(t)}\right)$$

The TF-IDF score is computed as:

$$TF - IDF(t, C_i) = TF(t, C_i) \times IDF(t)$$

Each caption is thus represented as a feature vector:

$$V_i = [w_1, w_2, \dots, w_m]$$

where

m denotes the vocabulary size.

w_k represents the TF-IDF weight of term k.

The memory grouping mechanism is represented as:

$$F: V_i \rightarrow G$$

where,

G represents the structured memory group determined by assigned labels and event metadata.

V _i provides contextual enhancement for search and similarity-based organisation.

The cosine similarity measure is used between the memory vectors as follows:

$$Sim(V_i, V_j) = \frac{V_i \cdot V_j}{|V_i| \cdot |V_j|}$$

If,

$$Sim(V_i, V_j) > \tau$$

where,

τ is the predefined similarity threshold.

The retrieval function can be expressed as:

$$R(Q) = \{M_i \mid relevance(V_i, Q) > \delta\}$$

where,

Q represents the user query.

V_i represents the TF-IDF vector of memory entry M_i.

δ is the predefined relevance threshold.

The computational complexity of TF-IDF vectorisation can be approximated as:

$$O(Nm)$$

where,

N represents the total number of memory entries.

m represents the vocabulary size.

4. Results and Discussion

The proposed NeuroNimbus framework was evaluated using a dataset consisting of 125 memory entries, including person-centred and event-centred memories. The characteristics of the experimental dataset are summarised in Table 1.

Table 1. Summary of the Experimental Dataset

Dataset Attribute	**Value**
Total Memory Entries	125
Person-centered Memories	75 (60%)
Event-centered Memories	50 (40%)
Data Type	Image + Caption
Additional Metadata	Person Label, Event Title, Date, Notes

The experimental results indicate stable, consistent system behaviour across all modules. The Memory Categorisation module performed effectively in grouping captions with contextual markers. The Duplicate Detection module successfully avoided redundant storage of similar images using cosine similarity thresholds and maintained multi-label associations when necessary. The Keyword Extraction module was slightly sensitive to language variations, including incomplete captions and minor spelling inconsistencies. However, normalisation and stop-word filtering improved the quality of keyword extraction as given in Table 2 and Figure 2.

Table 2. Module-wise Performance Evaluation

Module	**Accuracy (%)**
Keyword Extraction	87.6
Memory Categorization	90.8
Duplicate Detection	92.3

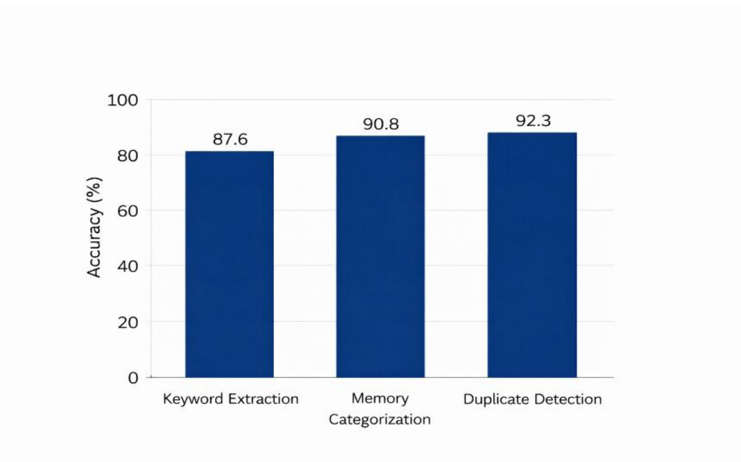

Figure 2. Performance comparison of NeuroNimbus modules based on evaluation accuracy.

Cloud synchronisation remained stable during all experiments. There were no instances of cross-patient data leakage and authentication errors. Multi-user experiments showed acceptable latency and stable repository updates. User-level experiments also validated the effectiveness of person-label, event category, and keyword-based memory grouping for improved accessibility and easier search. The memory repository organisation improved the usability of cognitive support applications. Additionally, the overall functional accuracy of the proposed framework was calculated as the average of the three modules of interest. The proposed system achieved an overall functional accuracy of 90.2%**,** indicating stable and reliable performance in structured digital memory reconstruction tasks. The experimental results demonstrate that NeuroNimbus successfully integrates NLP-based semantic analysis, redundancy control via similarity measures, structured categorisation, and secure cloud storage to build a functional digital memory reconstruction system.

5. Conclusions

This paper introduced NeuroNimbus, a cloud-assisted intelligent framework for structured digital memory reconstruction. The proposed system incorporates TF-IDF-based keyword extraction, cosine-similarity-driven redundancy detection, structured person- and event-based grouping based on assigned labels and metadata, and role-based cloud storage within a single framework. The experimental results demonstrated that the system exhibited stable functional characteristics across all modules. The keyword extraction module extracted appropriate descriptors from user-generated captions, and the memory categorisation module enabled structured grouping of memories into meaningful person- and event-based categories. The redundancy detection module reduced redundant storage by using a similarity threshold, thereby maintaining repository consistency. Rather than relying on computationally complex deep learning models, the framework emphasises interpretability, lightweight semantic processing, and deployability. This makes the system applicable in the healthcare setting, where computational complexity and resource management are of concern. The organised storage and retrieval functionality reduces caregiver workload and enhances accessibility for people with memory impairments. Although the current implementation demonstrates feasibility and stability, there are still some avenues for future improvements. The addition of transformer-based contextual embeddings can increase semantic complexity and context understanding. Incorporating speech-to-text functionality can increase accessibility for people with limited typing ability. Further enhancement of memory organisation through contextual tagging with temporal or location metadata can also be explored. Multilingual support and integration with healthcare information systems can also increase the applicability of the framework in the healthcare setting. From a practical perspective, the framework's lightweight architecture makes it suitable for real-world health environments, such as small clinics, assisted living facilities, and home care settings. The absence of large training datasets and computationally intensive deep learning models makes the framework suitable for environments with low technical resources. Therefore, the NeuroNimbus framework presents a suitable solution for long-term cognitive support. In summary, NeuroNimbus provides a scalable and patient-centric foundation for AI-assisted digital memory management. The system illustrates the real-world viability of integrating light NLP methodologies with secure cloud infrastructure to facilitate long-term cognitive care.

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