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MEDI-NET: CLOUD-BASED FRAMEWORK FOR MEDICAL DATA RETRIEVAL SYSTEM USING DEEP LEARNING

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Keywords: Medical record retrieval; Deep learning; Health Records; Indexing; Inception ResNet.

Medical data retrieval is becoming increasingly crucial, aiding physicians and domain experts in more effectively accessing knowledge and information related to medicine and facilitating informed decision-making. The centralized architectures need help with scalability and real-time indexing, leading to extended retrieval times and decreased efficiency. To address these issues, a novel MEdical Data retrieval using Inception resNET (MEDI-NET) has been proposed to retrieve medical data efficiently. The proposed system introduces a deep learning network for a dynamic poly-indexing model and concurrent indexing, ensuring the real-time retrieval of the latest medical records. EMRBots and MIMIC-III are the two datasets used to compare the performance of the proposed MEDI-NET approach with existing MRCG, HCAC-EHR, and FedCBMIR method, which is implemented using Python. The effectiveness of the proposed MEDI-NET approach has been determined using evaluation metrics such as precision, accuracy, recall, F1-score, indexing time, and retrieval time. Comparative analysis with existing methods demonstrates superior precision, accuracy, recall, and F1 score for the proposed method. Additionally, the proposed system exhibits reduced indexing and retrieval times, showcasing its efficiency in handling large-scale medical data. The proposed MEDI-NET approach's accuracy is 0.60 %, 9.87 %, and 21.1 % higher than the existing MRCG, HCAC-EHR, and FedCBMIR techniques, respectively.

1. INTRODUCTION

Medical record retrieval is a challenging task of negotiating bureaucracy and collaborating with different facilities to retrieve vital medical records for legal proceedings [1]. Technology integration has become crucial in the rapidly changing healthcare sector to improve patient care, boost medical research, and expedite operations [2]. Adopting electronic medical data retrieval (EMDR) technologies is crucial to this digital revolution [3]. In medical practice, electronic medical records are becoming more and more prevalent. They offer a rich and relatively new resource for clinical research. [4,5]. In the healthcare [6] ecosystem, medical data retrieval is the process of gathering, arranging, and obtaining information from various sources [7]. Some sources include electronic health records (EHRs), real-time monitoring devices, genetic data, diagnostic imaging, and patient-reported outcomes [8]. The main goal of medical data retrieval is to provide accurate and thorough information to healthcare practitioners so they may make well-informed judgments [9].

Deep learning [10] is useful for natural language processing (NLP) tasks and medical imaging. Information extraction from unstructured data in clinical notes and electronic health records depends heavily on NLP activities. [11]. It can identify complex correlations and extract pertinent information from data, which enhances our comprehension of a patient's medical history. Cloud [12] platforms built on Hadoop are commonly employed in the medical industry. In this case, the large-scale MDF documents are stored on HDFS, and the index files are created using the MapReduce architecture [13].

Efficiently retrieving pertinent medical records is hindered by the overwhelming volume of data, requiring healthcare providers to invest substantial time searching through extensive patient records [14]. Due to lengthy index-building processes, centralized medical record retrieval architectures need help to scale for massive data volumes, impeding real-time indexing of the latest relevant entries. Medical terminology's inherent complexity and ambiguity further complicate achieving high-quality medical searches [15]. To overcome these challenges, a novel MEDical data retrieval using Inception resNET (MEDI-NET) has been proposed to retrieve medical data efficiently. The contributions of the paper are as follows:

- Initially, the input query is preprocessed using Normalization, Tokenization, Word Removal, and Stemming techniques for accurate medical data retrieval.
- Using the bag of words technique, features are retrieved from the preprocessed data and fed into the Inception ResNet, while the search cluster receives the search request.
- The medical reports stored in the cloud are indexed using the poly-indexing model and concurrent indexing and stored in Hadoop: HDFS as index nodes. From Hadoop, the reports are clustered in the search cluster based on index loading and merging similarities.
- Similar data in the search cluster is retrieved based on the query request. Subsequently, weights are assigned based on time, and the data is re-ranked according to similarities. This re-ranked data is then sent as a response to the Inception ResNet.
- Finally, the response to the user query is displayed in the web browser using a report visualization template.

The remaining portion of this research is explained as follows: section 2 examines the research using the literature as a basis. Section 3 explains the proposed MEDI-NET system in detail. Section 4 contains the results and discussion, whereas Section 5 is the conclusion.

2. LITERATURE SURVEY

Several recent studies have utilized several techniques to retrieve medical data. The following section covers some current evaluation approaches and their disadvantages.

In 2019, [16] proposed a blockchain-based solution that protects privacy when retrieving medical images. The 14.65 s retrieval time affirms the approach's consistency. IoT uploads medical images, and smart contracts enable efficient retrieval based on similarity. The drawback is that huge

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image-related transaction time issues reduce system effectiveness.

In 2021, [17] proposed a framework called MRCG that incorporates the interaction between several gallery photos in the graph structure to combine Graph Neural Network (GNN) and Convolutional Neural Network (CNN). According to experimental results on several benchmark datasets, the suggested method can achieve 88.64 %. Additionally, the MRCG can surpass all baseline models compared to other cutting-edge models.

In 2021, [18] proposed a comprehensive method for retrieving medical images. The suggested method uses a unique deep network to classify the input query image. According to performance evaluation, the suggested RetrieveNet performs better for retrieving medical images than other current techniques. The suggested RetrieveNet achieves an average retrieval accuracy of 92.46 %.

In 2022, [19] developed the HCAC-HER algorithm, a hybrid cryptographic access control to retrieve electronic health records safely. The outcome section made it abundantly evident that the projected HCAC: EHR approach performed well compared to other hybrid cryptography algorithms. The results show that this method efficiently retrieves data and offers improved security.

In 2022, [20] suggested an unsupervised strategy based on spatial matching between the visual terms for content-based medical image retrieval (CBMIR). The experiment showed that the suggested location-based strategy could recover images from anatomically varied multimodal medical images with greater accuracy.

In 2022, [21] suggested a sophisticated content-based picture retrieval system that combines a bag of visual words with spark map reduction to achieve excellent accuracy for large amounts of data. With a 97.7 % accuracy rate, the suggested methodology outperforms the current classification technique for locating the image within the sizable database.

In 2023, [22] suggested a federated content-based medical image retrieval (FedCBMIR) program that uses FL to overcome the challenges of collecting a diverse medical data set for CBMIR model training. Using a generalized model, FedCBMIR achieves 96 %, 98 %, 97 %, and 94 % F1S in the BreaKHis experimentation and does it in 25.53 fewer training hours.

However, several related studies have been conducted to retrieve medical data based on the search query. Moreover, the existing methods have several disadvantages, such as less accuracy, increased indexing and retrieval time, *etc*. This paper proposes the MEDI-NET technique to eliminate these disadvantages, which are explained in the following section.

3. MEDI-NET APPROACH

This paper proposes a novel MEdical data retrieval using inception resNET (MEDI-NET) to retrieve medical data efficiently. The input query is initially preprocessed using normalization, tokenization, word removal, and stemming techniques for accurate medical data retrieval. From the preprocessed data, features are extracted using the bag of words technique, and the extracted features are given as input to the inception ResNet, and the search request is given to the search cluster. The medical reports stored in the cloud are indexed using the poly-indexing model and concurrent indexing and stored in Hadoop: HDFS as index nodes. From Hadoop, the reports are clustered in the search cluster based on index loading and merging similarities. Based on the query request, comparable data in the search cluster is retrieved. Subsequently, weights are assigned based on time, and the data is re-ranked according to similarities. This re-ranked data is then sent as a response to the inception ResNet. Finally, the response to the user query is displayed in the web browser using a report visualization template. Figure 1 depicts the architecture of the proposed MEDI-NET approach.

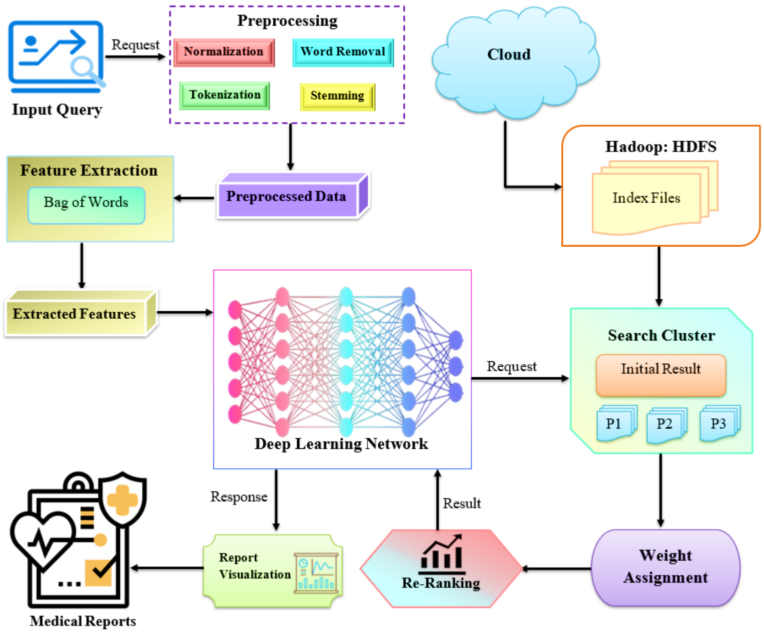


Fig. 1 – Architecture of the proposed MEDI-NET approach.

3.1 PREPROCESSING

Preprocessing is vital in improving input query consistency, manageability, and suitability for retrieval operations. The input queries are preprocessed using Normalization, Tokenization, Word Removal, and Stemming techniques to make the query in a suitable format.

3.1.1 NORMALIZATION

Normalization requires the simultaneous completion of multiple tasks. All text must be converted to uppercase or lowercase, numerals must be changed to words, and punctuation must be removed. As a result, every text will undergo more consistent pre-processing.

3.1.2 TOKENIZATION

Tokenization divides a text into meaningful pieces while maintaining its meaning. Long paragraphs, also known as text chunks or chunks, are split up into tokens, or sentences, at this stage. You can break these statements down into their component words as well.

3.1.3 WORD REMOVAL

Repeated words are eliminated from the text throughout this phase. Many stop words are used, including "are," "of," "the," and "at." As a result, these must be taken out of the text.

3.1.4 STEMMING

Words in multiple tenses are reduced to their most basic forms through stemming, which removes needless computations. Stemming aims to group words with similar meanings, even with different inflections or derivations.

3.2 FEATURE EXTRACTION

The preprocessed data undergoes feature extraction using bag of words (BoW) techniques. The goal of feature extraction is to provide a set of pertinent and instructive characteristics that can be utilized as input for deep learning networks from the preprocessed input data.

3.2.1 BAG OF WORDS (BOW) TECHNIQUE

The bag of words (BoW) is a straightforward and widely used feature extraction tool in NLP. The BoW algorithm ignores word order and focuses exclusively on word frequency to convert a text passage into a numerical vector. The formula for the bag of words representation of a document is

$$BoW(q_o) = \\ = [count(w_{o_1}, q_o), count(w_{o_2}, q_o) \ldots\ldots, count(w_{o_m}, q_o)], \quad (1)$$

where m represents vocabulary size and the query as q_0, $bow(d_o)$ represents the bag of words representation. Text tokenization is segmenting text into words using white space and punctuation as delimiters. A vocabulary is formed by treating each word as a unique entity.

Using the BoW technique, every input query is represented by a numerical vector, resulting in a fixed feature set. The length of each position in the vector, which represents a separate word, reflects the total vocabulary. Word frequency in the query is indicated by values in the vector. The BoW design is given by

$$y_i = [y_1, y_2, y_3, \ldots \ldots y_{ni}]. \quad (2)$$

Let n denote the general quantity of distinct words in the vocabulary. The detailed processing of the proposed system is shown in Fig. 2.

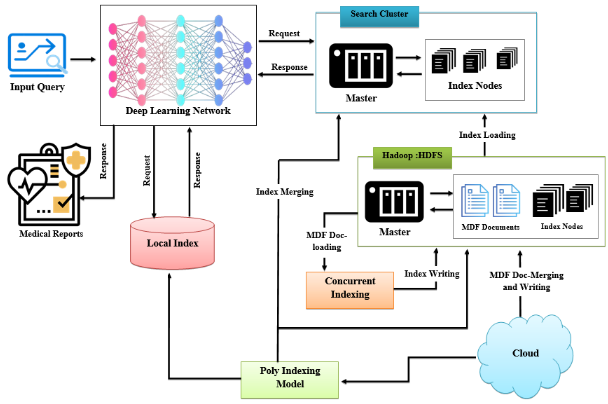


Fig. 2 – Detailed processing of proposed MEDI-NET approach.

3.3 INCEPTION RESNET

The Inception-ResNet architecture expands the inception structure to incorporate residual learning. The stem, the inception block, and the reduction block are the three components that make up an Inception ResNet. The deep convolutional layers comprise two max-pooling and zero convolutional layers to prepare the raw data for entry into the Inception-ResNet blocks. This final component is the prediction layer, which includes the SoftMax and pooling layers. The Inception ResNet receives the feature extracted query as input. The Inception ResNet block is detailed in Fig. 3.

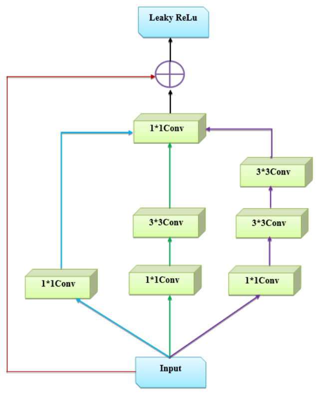


Fig. 3 – Architecture for inception Resnet.

The Inception-ResNet inception module displays two 3x3 kernels. Let y be the input query to an inception Resnet Block. The block's output (O(y)) is obtained by passing y through a series of operations. The residual connection is then added to the output. Mathematically, this can be represented as:

$$O(y) = F(y) + y. \quad (3)$$

Here, $F(y) results\ from$ the operations performed on y. The complete architecture involves stacking multiple such blocks, and the final output is typically obtained by passing the input through several blocks.

3.3.1 QUERY SEARCH USING INCEPTION RESNET

The search query is given to the inception ResNet, and then the search request is given to search clusters and local indexes in the network to retrieve similar medical data based on the given text query.

3.4 INDEX PROCESSING

Index Processing incorporates a dynamic poly-indexing system and concurrent indexing. The latter ensures real-time indexing and retrieval of all MDF documents, enhancing efficiency and responsiveness.

3.4.1 CONCURRENT INDEXING

This section introduces an advanced MapReduce index method, including data shuffling and map-reduce calculations. MDF sequence files are read from HDFS, partitioned by map nodes, merged into index files, and deployed to the search cluster for enhanced queries. In the map stage, MDF document text becomes key-value pairs, capturing attributes like patient details. The Reduce task builds the index from the key-value list, segmenting values into words using a dictionary set and analyzer. Finally, index files are stored in HDFS for retrieval.

Algorithm 1: Map-Reduce Indexing

```
Input: MDF_name, i.e., MDFdocument file term;
    MDF_doc, i.e., details of a MDF file;
    E_dics, i.e., Expanded medical dictionary set.
Output: f_name, i.e., File term with a key-value list;
    Li <key value>, i.e., Key-value list from CDAdoc;
    L_docu, i.e., Lucene file name;
    I_files, i.e., index files of MDF_doc.
start
Li <key value>{ };
for each node n_j in MDF_doc do
   if (n_j is indexed) then
      Li <key value>.put(n_j.getName(), n_j.getValue());
   end if
end each
f_name, Li <key value> {MDF_name, L <key value>};
Indexer, Analyzer { };
for each dictionary e_dic in E_dics do
   Analyzer.add(e_dic);
end each
L_doc  { };
for each key-value l in Li <key value> do
   L_doc.put(l.getKey(), l.getValue());
end each
I_file Indexer.buildIndex(L_doc, Analyzer);
return {f_name, Li <key value>, L_doc, I_file};
finish
```

3.4.2 DYNAMIC POLY INDEXING SYSTEM

Dynamic poly indexing ensures real-time indexing and retrieval of the latest medical records through three index groups: local disk, memory, and cluster. Massive MDF documents are indexed by MapReduce when the system starts. A new thread loads index files into memory and generates them upon receiving a new document. When memory index files surpass a threshold, they merge into the disk index. Similarly, local disk index files combine into the search cluster during idle times. This multi-indexing technique guarantees real-time access to all MDF documents.

3.4.3 DATA RETRIEVAL

In medical retrieval, time is an extremely crucial component. The new MDF documents are generally more beneficial than the previous ones. As a result, we calculate each MDF document's weight using generate time as a factor. Equation (4) expresses the computation.

$$W(R_n) = \frac{WR_n(t) - M_{in}(t)}{M_{ax}(t) - M_{in}(t)} (W(R_n) \in [0,1]). \tag{4}$$

where $M_{ax}(t)$ is the most recent creation time of all documents, $M_{in}(t)$ is the earliest generate period of all documents, and $R_n(t)$ is the generating period of R_n. VSM is used to compute the resemblance $Title_{simi}(q, R_n)$ between q and the label. Select the highest-ranked documents from each system can be expected to perform more effectively. $P_{simi}(R_n, res)$ is determined using:

$$P_{simi}(R_n, res) = \frac{L(res) + P(res) - 1}{L(res)} \left(1 \le (res) \le L(res)\right). \tag{5}$$

Here, $P_{simi}(R_n, res)$ represents the position similarity of R_n in result res, where $L(res)$ denotes the result res length. The index number in result res is represented by $P(res)$. Each matching MDF document's similarity to the query q is calculated, and the results are reranked based on this similarity.

Algorithm 2: Data Retrieval

```
Input:
   q' = {qg', qb'} (Expanded query q')
   I = { I_disk, I_cluster, I_ram } (Site of index files)
Output:
   R = { R_disk, R_cluster, R_ram } (MDF documents matched the query)
start
initialize { R_disk, R_cluster, R_ram };
for each index I_i in I (i =ram, disk, cluster) do
   for each R_n in I_i do
      Score(R_n) <- 0;
      Score(R_n) <- BM25(q', R_n);
      Scores.put(R_n, Score(R_n));
   finish for
   if (Scores< R_n, Score(R_n)> is not empty) then
      R.put(Scores.sort());
   finish if
finish for
return R;
finish
```

Finally, the weight of each MDF document is calculated based on generation time, emphasizing the significance of recent records.A vector space model is utilized to ascertain the partial similarity links between the query and MDF documents, improving the ranking and relevance of returned results.

3.4.4 REPORT VISUALIZATION

Medical reports are displayed using a template-based visualization technique for user-friendly examination. Various MDF document types have distinct data elements and presentation styles, addressed by templates created with CSS and XSL. Retrieved data is transformed into HTML and presented on a webpage, as illustrated in Fig. 4.

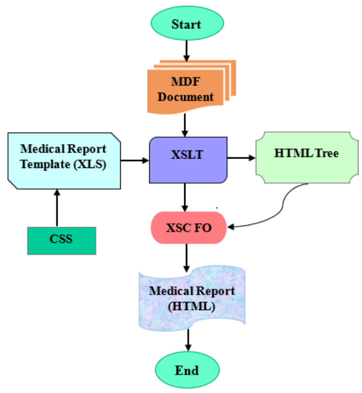


Fig. 4 – Medical report's visual workflow.

The visualization includes XSL FO, HTML, XSLT, and CSS-based templates for medical reports. These reports are reconstructed from MDF/XML documents, focusing on necessary data extracted through indexing from the original clinical records. The final medical report is displayed on a web browser, providing users with a streamlined and informative view.

4. RESULTS AND DISCUSSION

This section will include the proposed MEDI-NET method's results and a comparison with existing MRCG [17], HCAC-EHR [19], and FedCBMIR [22] methods. Python was used to accomplish the proposed MEDI-NET method. The proposed MEDI-NET method and the performance of existing methods are demonstrated using the EMRBots and MIMIC-III datasets.

4.1 DATASET DESCRIPTION

The EMRBots dataset includes a variety of medical records, including demographics of the patients, diagnoses, treatments, and other pertinent clinical data. With more than 100,000 records from different medical facilities. The MIMIC-III comprises de-identified medical records from more than 40,000 between 2001 and 2012. Over 38,000 adult and about 20,000 newborn patients comprise the 58,000 ICU admissions.

4.2 PERFORMANCE ANALYSIS

The retrieval result of the proposed MEDI-NET method using the dataset is shown in this section. The retrieved data is shown on the webpage, a user-friendly access interface.

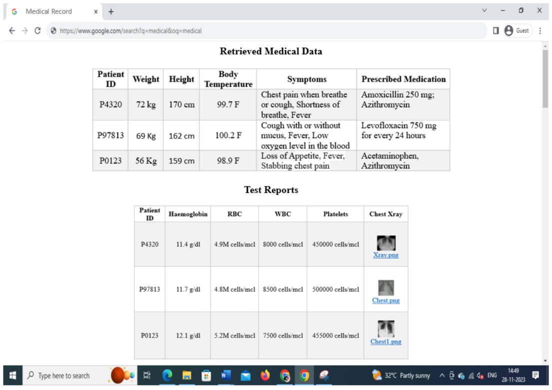
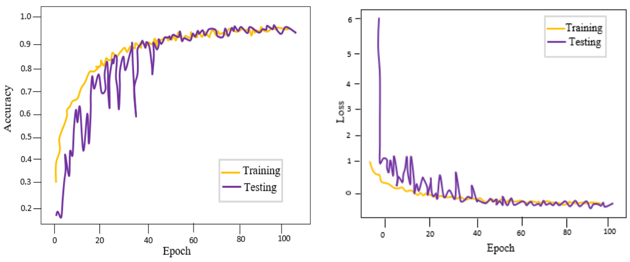


Fig. 5 – Retrieved medical data on a web page.

Figure 5 represents the visual presentation of medical data retrieved through the proposed system, particularly for a query related to pneumonia; the medical details, like the patient's weight, height, body temperature, symptoms, and prescribed medication, are shown on the web page. The test reports of the patients with pneumonia are also retrieved and displayed on the webpage.



(a) (b)

Fig. 6 – (a) Accuracy curve, (b) Loss curve.

Figure 6 displays training and test datasets alongside accuracy and loss curves. Subfigure (a) reveals increasing model accuracy on both sets during training epochs. A decreasing trend in training and validation losses is seen in Subfigure (b). These curves guarantee excellent performance for medical image retrieval tasks by offering insightful information about the model's learning process.

4.3 COMPARATIVE ANALYSIS

The simulations in this section evaluate the effectiveness of the proposed MEDI-NET method. Several criteria, such as precision, accuracy, recall, F1 score, indexing time, and retrieval time, are used to assess the proposed approach.

Figure 7 illustrates a precision comparison using EMRBots and MIMIC-III against existing methods like MRCG [17], HCAC-EHR [19], and FedCBMIR [22] for medical record retrieval. Our proposed MEDI-NET method demonstrates superior precision, outperforming existing techniques [23]. Leveraging EMRBots and the MIMIC-III dataset, our approach ensures more accurate and reliable retrieval of medical records.

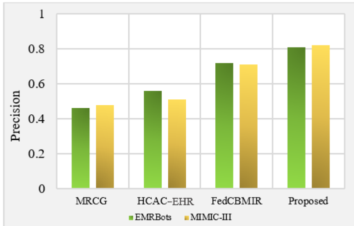


Fig 7 – Comparison in terms of Precision using different datasets.

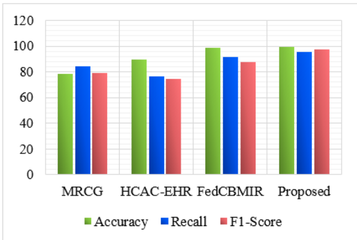
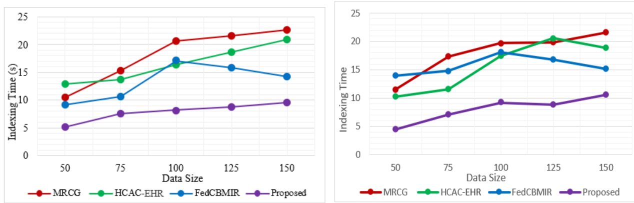


Fig 8 – Comparison in terms of performance.

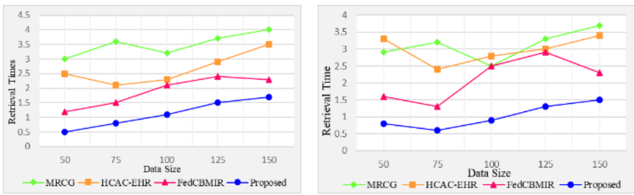
Figure 8 shows the comparison performance of the proposed MEDI-NET method with existing MRCG [17], HCAC-EHR [19], and FedCBMIR [22] methods. MEDI-NET outperforms existing methods with 0.60 %, 9.87 %, and 21.1 % higher accuracy. Recall for MEDI-NET is 95.42 %, precision, and F1-score are 93.8 %, and overall performance surpasses existing techniques.



(a) (b)

Fig. 9 – Comparison in terms of indexing time using (a) EMRBots dataset (b) MIMIC-III dataset.

In Fig. 9, a comparative analysis of indexing time using the EMRBots and MIMIC-III datasets shows the proposed MEDI-NET method outperforming MRCG, HCAC-EHR, and FedCBMIR. MEDI-NET demonstrates significantly shorter indexing times, highlighting its efficiency in medical record retrieval.



(a) (b)

Fig. 10 – Comparison of retrieval time using: (a) EMRBots dataset, (b) MIMIC-III dataset.

Fig. 10 illustrates a comprehensive comparison of retrieval times using the EMRBots dataset and MIMIC-III dataset between the proposed MEDI-NET and existing MRCG [17], HCAC-EHR [19] and FedCBMIR [22] methodologies. Our proposed system consistently achieves faster retrieval times, outperforming existing systems, and excels in processing EMRBots and MIMIC-III datasets.

5. CONCLUSION

This paper proposes a novel MEdical data retrieval using Inception resNET (MEDI-NET) to retrieve medical data efficiently. The proposed system involves a multi-step approach, starting with query preprocessing techniques and utilizing the BoW technique for feature extraction. Integrating Inception ResNet enhances natural language processing tasks and medical data analysis. Using a dynamic poly-indexing system and concurrent indexing ensures real-time retrieval of the most recent medical records, addressing the scalability issues of centralized architectures. Python was used to accomplish the proposed MEDI-NET method and demonstrates its performance alongside existing methods using EMRBots and MIMIC-III datasets. The proposed approach performs better in terms of precision, accuracy, recall, F1 score, indexing time, and retrieval time when compared to current techniques. The proposed method's accuracy is 0.60 %, 9.87 %, and 21.1 % higher than the existing MRCG, HCAC-EHR, and FedCBMIR techniques. Future work will expand the proposed system's capabilities to handle and retrieve data from various modalities.

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