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Development and evaluation of a model for effective translation of patient complaints in natural language to relevant medical terms by using following NLP techniques

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ABSTRACT

It is critical for healthcare services to comprehend the complaints of patients spoken in their own language and convert them into medical terms. This paper aims to develop and evaluate a model to translate the patients' complaints in Marathi to proper medical terms. There are different ways to do it, each with its pros and cons. Examples of such techniques are direct translation based on word dictionaries, rule-based extraction, Ontology mapping as well as Ontology mapping with Named Entity Recognition (NER). The model will enable doctors and health care systems to better comprehend the problems of patients by intelligently using texts with natural language processing (NLP) and medical vocabularies. It will also assist in keeping correct medical records, facilitate improved medical decision making, and streamline healthcare systems.

Keywords: Patient Complaints, Medical Terminology, Marathi Language, Natural Language Processing (NLP), Healthcare, Medical Records, Symptom Translation, Machine Learning.

1. INTRODUCTION

When patients go to a doctor, they present their health problems in their own words, called "complaints." These complaints guide doctors on symptoms so they can make appropriate diagnoses. In a multilingual country such as India, where many people are conversant in Marathi, the effort to translate these everyday problems into proper medical definitions is hard work. Many countries around the world use consistent medical classification systems including SNOMED CT and ICD-10 for healthcare documentation.

The article describes various approaches for converting Marathi patient complaints into medical terminology. There are a few options to choose from with their pros and cons. These methods range from direct translation using word dictionaries, rule-based extraction, and ontology mapping, as well as a hybrid between mapping to ontology and Named Entity Recognition (NER).

One way to convert these user Marathi complaints to medical language is a dictionary-based approach. In this approach a dictionary is prepared containing Marathi words along with their corresponding medical terms in English. For example:

- "वेदना" → "Pain"
- "ताप" → "Fever"

Though simple, this method has downsides. It may not consider complex expressions, regional dialects or differences in descriptions provided by patients. Moreover, keeping a complete dictionary requires considerable effort and may still not cover all phrases [1].

1.1. Rule-Based Extraction

In this approach, predefined linguistic rules are used to identify medical terms in complaints written in Marathi. Patterns created by experts to identify symptoms and medical conditions. For example:

- **Complaint:** "माझ्याकंबरेलावेदनाआहे" (I have pain in my back)
- **Extraction:** "कंबरेला" (Back) → **Body Part**, "वेदना" (Pain) → **Symptom**

This method is time consuming, even as it works well in structured cases. Patients may describe their symptoms in different ways: language is malleable, making it impossible to cover every observation **[2]**.

1.2. Ontology Mapping

Ontology is a governed framework that connects words with medical concepts. When patient complaints include words such as "वेदना" (pain), they can be mapped to formal medical terms:

- "वेदना" → "Pain" (SNOMED CT Code: 22253000)

This approach ensures consistency between healthcare systems, making patient data more usable for diagnosis and for research." For Marathi, it takes considerable effort to build a detailed ontology as a lot of mapping of anatomical lexicon and disease types are required [3].

1.3. Ontology Mapping with Named Entity Recognition (NER)

This method employs ontology mapping with Named Entity Recognition (NER) — a strategy through which critical medical terms in text can be identified. A trained model can automatically identify words pertaining to symptoms, body sites, or conditions in input text, and link them to appropriate standard terms.

For example:

- **NER detects:** "वेदना" (Pain), "ताप" (Fever), "कंबरेला" (Back)
- Ontology mapping links them to: SNOMED CT or ICD-10 codes

Although this method is scalable and adaptable, it also relies on high quality training data and a well-defined medical ontology in Marathi [4].

Properly converted Marathi patient complaints into standardized text leads to better documentation by the health service provider, which ultimately improves diagnosis and can be used for research by the government or private agencies. The dictionary-based translation is relatively simple, but has no flexibility. Extraction based on rules works; however, it takes a lot of time and manual effort. Ontology mapping provides standardization but relies on a rich set of database. A more effective solution proposed by Huang, Zhang, Chen, and others integrates ontology mapping with Named Entity Recognition (NER) for automated and scalable medical translation.

Practical and efficient implementations of these approaches in real-world healthcare settings will require a robust backbone of linguistic data, domain-specific knowledge, and structured medical ontologies.

2. LITERATURE STUDY

2.1. Introduction to NLP in Healthcare: Natural Language Processing (NLP) is one of the most used techniques in healthcare applications today especially processing unstructed text, e.g. patient complaints, clinical notes, clinical record and so on. The initial step of this approach takes an encounter's chief complaint — an informal statement expressing a patient's concern — and converts it into health care standard patients descriptions (clinical coding like ICD-10 or SNOMED CT) for better clinical decision making, accurate diagnosis, and improved patient outcomes.

Key Concepts:

- **Chief Complaint (CC)**: Patient appends a chief complaint or the main complaint of a patient, typically described in free-form, sometimes when asked in colloquial language. Clinical documentation and healthcare management systems require converting this complaint into standard medical codes, such as the International Classification of Diseases, for usage.
- **Medical Terminology**: Global disease classification protocol and clinical terminology involve the use of medical terminologies like ICD-10 (International Classification of Diseases) and SNOMED CT. Mapping free-text complaints to these standard medical terminologies is necessary to preserve the consistency of diagnosis and treatment [5] [6].

2.2. Challenges in Translating Marathi Complaints

The translation of patient complaints in **Marathi**, a regional language in India, presents several challenges:

- **Linguistic Complexity**: A lot of Marathi expressions exist, which are also highly contextual. Furthermore, patient complaints also often contain colloquial and informal language which makes it difficult to map to standard terms. The same goes for the Marathi word for "headache", where several synonyms exist, depending on geography and someone's creativity.

- **Data Scarcity**: There is currently a shortage of annotated and large datasets for Marathi healthcare text. Unlike high-resource languages such as English where a lot of data is available, Marathi is a low-resource language and therefore building deep learning models which can provide decent accuracy with very little data is challenging.
- **Ambiguity in Expression**: Patients often describe symptoms in vague terms, making it difficult to directly map them to standardized medical terminologies **[7] [8].**

2.3. Approaches to NLP for Translating Marathi Complaints

To address the challenges outlined, several approaches are used to translate Marathi complaints into standardized medical terminology. These can be broadly categorized into **rule-based**, **statistical**, **neural**, and **hybrid** approaches:

2.3.1 Rule-Based Systems

Early methods relied on predefined rules that map complaints to medical codes manually. These systems work well with limited vocabulary but fail to generalize well to new or informal expressions commonly used in patient complaints**[9][10].**

Example: A rule-based system might match the Marathi complaint "मला डोकं दुखत आहे" (I have a headache) to an ICD-10 code like **G44.1** (Cluster headache), based on a dictionary of symptoms and codes.

2.3.2 Statistical Machine Translation (SMT)

Statistical methods rely on probability to match Marathi complaints with their corresponding medical terms. However, this requires a large parallel corpus, which is often not available for Marathi medical texts**[11][12].**

Example: A statistical system might align parallel Marathi-English corpora to translate a Marathi complaint into medical terms. This approach needs large amounts of parallel data, which is a challenge for low-resource languages like Marathi.

2.3.3 Neural Machine Translation (NMT)

NMT applies deep learning models **seq2seq** (sequence-to-sequence) models/ transformers, which maps a translation between Marathi and medical terms. These models can capture context and semantic relations but require massive training data sets and computational resources 13.

Example: By processing large datasets of clinical texts, an NMT model could learn how to translate the input string **"सर्दी"** (cold) into its medical counterpart **J00** (**Acute nasopharyngitis).**

2.3.4 Hybrid Models

Hybrid systems implement a combination of rule-based methods and machine learning or deep learning models to get better accuracy. These systems utilise structured (e.g., medical vocabularies) and data- driven approaches to capture the complexity of real-world complaints [15] [16].

Example: A Hybrid model, where the model may first run some rule-based system to extract the major symptoms from the Marathi text (like ज्वर would mean fever) and then use something like a Weighted approach/Classifier to map to the right disease/medical code.

2.4. Medical Terminology Standardization

One of the most important steps is standardizing the patient complaints into medical codes, e.g., **ICD-10, SNOMED CT, or UMLS**. There have been great number of research initiatives being done on map the raw text to these structured terminologies. This is critical to building interoperable healthcare systems that can talk to each other across the world.

Example: For effective diagnosis and treatment documentation, a complaint like **किडनी दवते आहे** (Kidney pain) needs to be mapped to the appropriate ICD-10 code (**N20**) - in this case (**Kidney stone**)

In this work the Marathi patient complaints translated into NLP where the standard medical terminology is mapped to human readable patient complaints is quite an important area for research because providing safe clinical decision making can be made easier with this NLP mapping.

3. METHODOLOGY

Mapping patients' chief complaints into standardized medical lexicon is critical for informing communication and management in health care. In multilingual settings such as India, where patients might be describing symptoms in their vernacular, this is critical. Advanced Natural Language Processing (NLP) methods provide several variants to tackle this problem, including:

1. Direct translation using word dictionaries
2. Rule-based extraction

3. Ontology mapping
4. Ontology mapping combined with Named Entity Recognition (NER)

All methods have their own pros and cons which will be addressed below.

Before applying any method we first perform Pre-processing of Marathi Complaints.

- Algorithm 1: Pre-processing Complaints in Marathi
    - Input: Raw text data in Marathi (complaints dataset in CSV format)
    - Output: Cleaned, tokenized, vectored feature representation of complaints

```
Step I: Data Collection
    • 1. Load the dataset of complaints into a data structure (e.g., Data Frame)
    •   INPUT: CSV file with Marathi complaints
    •   OUTPUT: Data loaded into appropriate data structure
    • 2. Set the variable `data = load_dataset ("complaints.csv") `
Step II: Remove Immaterial Data
1. FOR each complaint `C` in dataset `data` DO:
   a. Remove non-language special characters (e.g., @, #, %, etc.)
      - Use regex: `C = remove_special_characters(C)`
   b. Remove irrelevant numbers (unless medically relevant)
      - Use regex to match irrelevant numbers
   c. Remove English text (if present)
      - Use regex to remove non-Devanagari characters
   END FOR
2. Cleaned Marathi text `cleaned_data`
Step III: Tokenization
1. FOR each cleaned complaint `C` in `cleaned_data` DO:
   a. Tokenize the text into individual words
      - Use Marathi tokenization library (e.g., indic-nlp-library)
      - Set `tokens = tokenize(C)`
   END FOR
2.  List of tokens for each complaint `tokens_list`
Step IV: Stop Word Removal
1. Load the Marathi stop words list `stop_words_list`
   - This is predefined.
2. FOR each list of tokens `T` in `tokens_list` DO:
a. FOR each token `t` in `T` DO:
IF `t` is in `stop_words_list` THEN:
Remove `t` from `T`
END IF
   END FOR
   END FOR
3. Filtered tokens list `filtered_tokens_list`
Step V: Stemming and Lemmatization
```

```
1. Load morphological analyzer for Marathi
   - This can be done using a tool like indic-nlp-library
2. FOR each list of filtered tokens `T` in `filtered_tokens_list` DO:
a. FOR each token `t` in `T` DO:
      Apply stemming/lemmatization on `t`
      - `stemmed_t = stem_or_lemmatize(t)`
   END FOR
   END FOR
3. Stemmed or lemmatized tokens `stemmed_tokens_list`
Step VI: Text Vectorization (Feature Extraction)
1. Select vectorization technique (Bag of Words, TF-IDF, or Word Embeddings)
   -  Use Bag of Words (BoW) or TF-IDF:
      Apply vectorization using scikit-learn's TF-IDF or BoW
2. Apply chosen technique to `stemmed_tokens_list`:
   FOR each list of tokens `T` in `stemmed_tokens_list` DO:
      - Apply vectorization
      - `feature_vector = vectorize(T)`
   END FOR
3.  Numeric feature vectors `feature_vectors`
Step VII: Final Output
      • 1. Save or store the processed data
   -: Save `feature_vectors` to a CSV file
2. Preprocessed data saved for further analysis
```

▪ Algorithm 2: Extracting Key Phrases from Chief Complaints in Marathi

```
Input: Raw text data in Marathi (complaints dataset in CSV format)
Output: Key phrases extracted from each complaint
Step I: Data Collection
1. Load the dataset of complaints into a data structure (e.g., DataFrame)
   INPUT: CSV file with Marathi complaints
   OUTPUT: Data loaded into appropriate data structure
      • 2. Set the variable `data = load_dataset ("complaints.csv")`
Step II: Pre-processing (Tokenization, Stop Word Removal, Lemmatization)
1. Follow Steps II-V from the **Pre-processing Complaints Algorithm** to clean the text, tokenize, remove stop words, and apply lemmatization or stemming.
   INPUT: Raw text data from complaints
   OUTPUT: Cleaned, filtered tokens `processed_tokens_list`
Step III: Phrase Extraction Using N-grams
1. Set the value of `n` for n-grams
2. FOR each list of tokens `T` in `processed_tokens_list` DO:
   a. Generate n-grams from `T`
      - Apply n-gram model: `ngrams_list = generate_ngrams(T, n)`
   END FOR
3. List of n-grams (phrases) for each complaint `ngrams_list`
Step IV: Statistical Phrase Selection (TF-IDF or Frequency-based)
1. Select a statistical method to rank key phrases:
a: Apply TF-IDF to rank phrases by importance
    - Use scikit-learn: `tfidf_model = TfidfVectorizer(ngrams_list)`
    -Fit model and extract top-ranked phrases: `tfidf_features = tfidf_model.fit_transform(ngrams_list)`
b: Use frequency-based ranking:
    - Count occurrences of each n-gram: `phrase_frequencies = Counter (ngrams_list)`
2. FOR each list of phrases `P` in `ngrams_list` DO:
a. Rank the phrases using the selected method
b. Extract top key phrases: `key_phrases = select_top_phrases(P)`
  END FOR
3.  Ranked key phrases for each complaint `key_phrases`
Step V: Filtering Out Non-informative Phrases
1. Load or create a custom dictionary of non-informative or irrelevant phrases
2. FOR each list of key phrases `K` in `key_phrases` DO:
a. FOR each phrase `p` in `K` DO:
     IF `p` is in the non-informative phrase dictionary THEN:
        Remove `p` from `K`
     END IF
  END FOR
  END FOR
3.  Filtered key phrases `filtered_key_phrases`
Step VI: Final Output
1. Save or store the extracted and filtered key phrases:
a: Save `filtered_key_phrases` to a CSV file
b: Insert `filtered_key_phrases` directly into the database
2. Filtered key phrases saved for further analysis
Algorithm 3: Mapping Key Phrases to Medical Key Terms (Organs, Symptoms, and Conditions)
Input: Extracted key phrases from Marathi complaints, predefined key terms (organs, symptoms, conditions, etc.)
Output: Mapped key phrases to medical categories (organs, symptoms, conditions)
Step I: Load Predefined Key Term Lists
1. Load predefined medical key terms for categories such as organs, symptoms, and conditions.
     a. Load organs list: `organs_list = load_from_file("organs_list.csv ")`
     b. Load symptoms list: `symptoms_list = load_from_file("symptoms_list.csv")`
c. Load conditions list: `conditions_list = load_from_file("conditions_list.csv")`
2.  Lists of predefined terms (organs, symptoms, conditions, etc.)
Step II: Pre-process Key Terms and Phrases (Stemming/Lemmatization)
1. Apply stemming or lemmatization to both the predefined key terms and the extracted key phrases to ensure consistency.
   FOR each list `L` in (organs_list, symptoms_list, conditions_list) DO:
```

```
a. Apply stemming or lemmatization: `stemmed_L = stem_or_lemmatize(L)`
   END FOR
   FOR each key phrase `P` in `extracted_key_phrases` DO:
 b. Apply stemming or lemmatization: `stemmed_P = stem_or_lemmatize(P)`
   END FOR
2.  Pre-processed lists of key terms and key phrases
Step III: Match Key Phrases to Categories Using Exact and Partial Matching
1. FOR each key phrase `P` in `stemmed_extracted_key_phrases` DO:
a. FOR each word `W` in `P` DO:
     i. IF `W` matches any term in `organs_list` THEN:
        Map `P` to the "Organ" category
     ii. ELSE IF `W` matches any term in `symptoms_list` THEN:
        Map `P` to the "Symptom" category

  iii. ELSE IF `W` matches any term in `conditions_list` THEN:
        Map `P` to the "Condition" category
iv. ELSE IF partial_match(`W`, any term in `organs_list`, `symptoms_list`, or `conditions_list`) THEN:
   Perform a fuzzy match and assign the most likely category
 END IF
   END FOR
   END FOR
2.  Key phrases mapped to respective categories
Step IV: Handle Ambiguity and Multi-category Matches
1. FOR each key phrase `P` that matches multiple categories (e.g., a word that can be both an organ and a symptom), DO:
a. Set a priority or confidence score for each category based on domain knowledge.
     Example: If a word is more likely to be a symptom than an organ, prioritize the "Symptom" category.
b. Apply ranking rules: `ranked_category = rank_by_confidence(P, [categories])`
c. Assign `P` to the category with the highest confidence score.
2.  Unambiguous mapping of key phrases to single categories
Step V: Store or Output the Mapped Phrases
1. Store the mapped key phrases in a structured format:
a. Save as CSV to a database:
     Example: `save_to_csv("mapped_key_phrases.csv", mapped_phrases)`
b. Store key phrases with their mapped categories for further analysis or visualization.
2. Finalmapped key phrases with corresponding categories (Organs, Symptoms, and Conditions)
```

Methods

To develop and evaluate a model for effective translation of patient complaints in natural language to relevant medical terms by using following NLP techniques.

3.1. Direct translation using word dictionaries

A straightforward approach to translation involves bilingual dictionaries, mapping Marathi words to their English equivalents.

- Algorithm 4: Converting Extracted Key Phrases to English Medical Terms

Input: Chief complaints in Marathi (raw text)

Output: Extracted key phrases translated to English medical terms

Step I: Pre-process the Input Text

1. Clean and normalize the raw Marathi text.

a. Remove unnecessary punctuation, symbols, and special characters using regex.

Example: `clean_text = clean_raw_text(raw_text)`

b. Tokenize the text into words or phrases.

Example: `tokens = tokenize (clean_text)`

c. Apply stemming or lemmatization to reduce word forms to their root.

Example: `normalized_tokens = stem_or_lemmatize(tokens)`

2. Cleaned and tokenized text ready for key phrase extraction

Step II: Extract Key Phrases (NER)

1. Use Named Entity Recognition (NER) or rule-based extraction to identify key phrases like symptoms, conditions, medications, or anatomical organs.

a. Load a custom-trained NER model for the medical domain in Marathi OR apply rule-based extraction.

Example: `ner_model = load_model("marathi_medical_ner_model")`

b. Run the model or rules to extract key medical phrases from the text.

Example: `extracted_phrases = ner_model.extract_entities(tokens)`

c. Collect the extracted phrases categorized by type (symptom, organ, condition).

2. List of extracted key phrases (symptoms, organs, conditions, etc.)

Step III: Load the English Medical Term Dictionary

1. Load a bilingual medical term dictionary that maps Marathi medical terms to their English equivalents.

a. The dictionary contains Marathi medical phrases as keys and corresponding English terms as values.

Example: `medical_dict = load_dictionary("marathi_to_english_medical.json")`

b.Set up a fast lookup mechanism (e.g., a hash map or dictionary) for quick translation of Marathi terms.

2. Bilingual medical term dictionary ready for mapping

Step IV: Translate Extracted Phrases to English

1. FOR each extracted key phrase `P` in `key_phrases` DO:

a. Direct Dictionary Lookup:

i. IF `P` exists in the bilingual medical dictionary, THEN:

Translate `P` to the corresponding English term.

b. Synonym or Fuzzy Match:

i. IF no exact match is found in the dictionary, search for synonyms or use fuzzy matching algorithms.

ii. IF a similar term is found, assign the closest match as the English term.

c. Handling Complex Phrases:

i. For multi-word Marathi phrases, attempt to map each component (e.g., "डोके दुखणे" → "Head Pain").

ii. Combine the translations of individual words to form the final English phrase.

d. Store the result:

2. List of translated key phrases in English

Step V: Post-processing and Validation

1. After translation, perform post-processing on the translated terms:

a. Remove duplicates or redundant translations.

Example: IF two phrases translate to the same term, keep only one.

b.Validate the translated terms using a medical dictionary or ontology to ensure correctness.

Example: Double-check that the terms are valid medical terms by comparing them with a trusted medical source.

c. Handle variations in terminology (e.g., British vs. American English) to standardize terms.

Example: Convert "favourite" → "favorite" if required.

2. Clean and validated English medical terms

Step VI: Store and Output the Translated Phrases

1. Store the final list of translated medical terms in English:

a. Save the results in a structured format such as CSV or JSON for further analysis.

Example: `save_to_csv ("translated_medical_terms.csv", translated_phrases)`

b. Optionally, insert the translated terms into a database or use them for downstream tasks like ontology mapping or medical records.

Example: `insert_into_db("clinical_db", translated_phrases)`

2. Final list of translated medical terms in English

Conclusion

It is super easy to implement and we can assign it in a decent way for basic medical terms. But this comes at the cost of its ability to read the context of words, rendering it ineffective at reading informal or patient-generated language. Moreover, as a solution, it does not scale to large medical databases.

3.2. Rule-based extraction

This approach is based on a set of predetermined linguistic rules for extracting medical data from patient complaints [19].

Algorithm 5: Rule-Based Extraction of Medical Phrases from Chief Complaints

Input: Chief complaints in Marathi (raw text)

Output: Extracted medical phrases based on rules (e.g., symptoms, organs, conditions)

Step I: Define Rule Set for Extraction

1. Define a set of rules for identifying key phrases, such as symptoms, organs, or conditions. Each rule consists of linguistic patterns and domain-specific terms.

a. Symptom identification rules:

Example:

- Look for keywords like "दुखणे", "खोकला", "ताप", "सुज"

- Identify adjective + noun combinations (e.g., "जास्त दुखणे")

b. Organ identification rules:

Example:

- Look for anatomical terms such as "डोके", "हृदय", "फुफ्फुसे"

- Identify noun phrases that refer to organs.

c. Condition identification rules:

Example:

- Match against known disease names (e.g., "मधुमेह", "हृदयविकार")

2. Develop regular expressions (regex) or pattern-based rules for each entity type.

3. Predefined rule set for medical phrase extraction

Step II: Pre-process the Text

1. Clean and normalize the raw input text:

a. Remove unnecessary symbols, punctuation, and non-Marathi characters using regex.

b. Tokenize the text into words or phrases for rule application.

c. Optionally, apply stemming or lemmatization to standardize word forms.

2. Cleaned and tokenized text ready for rule-based extraction

Step III: Apply Rules to Extract Medical Phrases

1. FOR each token or phrases `T` in the `normalized_tokens` DO:

a. Apply symptom rules:

i. IF `T` matches a predefined symptom pattern or keyword THEN:

Mark `T` as a symptom.

Example: IF `T` matches "दुखणे", THEN extract as a symptom.

b. Apply organ rules:

i. IF `T` matches a predefined organ pattern or anatomical term THEN:

Mark `T` as an organ.

Example: IF `T` matches "डोके", THEN extract as an organ.

c. Apply condition rules:

i. IF `T` matches a known condition or disease term THEN:

Mark `T` as a medical condition.

Example: IF `T` matches "हृदयविकार", THEN extract as a condition.

d. Handle complex patterns (e.g., adjective + noun):

i. IF a complex phrase like "जास्त दुखणे" matches a symptom pattern THEN:

Extract both parts (adjective + noun) as a symptom.

2. List of extracted medical phrases categorized by type (symptoms, organs, conditions)

Step IV: Handle Multi-word Phrases and Contextual Patterns

1. Use multi-word phrase rules to capture relevant entities that span more than one word.

a. IF a phrase includes both a symptom and an organ (e.g., "डोके दुखणे"), THEN:

Extract the entire phrase as a symptom related to the organ.

b. Identify and capture context around the key phrases to ensure accurate extraction.

Example: Use patterns such as [adjective] + [symptom] or [noun] + [condition].

2. Extended medical phrases with contextual information

Step V: Post-processing and Filtering of Extracted Phrases

1. After extraction, apply post-processing rules to refine the results:

a. Remove or merge duplicate or overlapping phrases.

b. Filter out irrelevant phrases using a predefined list of stop phrases or non-informative terms.

Example: Eliminate phrases like "आहे", "असलेले" which do not add medical information.

c. Validate the extracted phrases by comparing them against a medical dictionary to ensure correctness.

2. Final list of validated and filtered medical phrases

Step VI: Store and Output Extracted Phrases

1. Store the final list of extracted medical phrases in a structured format:

a. Save as CSV, JSON, or insert into a database for further analysis.

Example: `save_to_csv ("extracted_medical_phrases.csv", extracted_phrases)`

b. Output the results for use in downstream tasks such as ontology mapping or NLP analysis.

2. Structured output of extracted medical phrases categorized by type

Conclusion

This method provides high accuracy when applied to structured text and works well for domain-specific applications. However, it requires significant effort to create and maintain. It is effective in controlled environments but struggles with informal language variations and lacks flexibility in adapting to evolving patient expressions.

3.3. Ontology Mapping

Ontology mapping aligns extracted patient complaints with standardized medical concepts like SNOMED CT and ICD-10[20][21].

- Algorithm 6: Ontology Mapping Algorithm for SNOMED-CT

```
Input: Key phrases extracted from complaints, SNOMED-CT ontology database
Output: Key phrases mapped to SNOMED-CT codes
Step I: Pre-load SNOMED-CT Ontology
1. Load SNOMED-CT ontology into the system.
a. Import SNOMED-CT concepts, including synonyms, preferred terms, and descriptions.
  Example: Load from a structured dataset like JSON or from a database.
b. Set up an efficient data structure (e.g., trie or hash map) to store SNOMED-CT concepts for fast matching.
    Example:
  `snomed_ct = load_snomed("snomed_ct_ontology.json")`
2.  SNOMED-CT concepts loaded and structured for fast lookup
Step II: Pre-process Extracted Key Phrases (Stemming/Lemmatization)
1. Pre-process the extracted key phrases using the same stemming or lemmatization technique as used in previous algorithms.
  Example: `processed_key_phrases = stem_or_lemmatize(extracted_key_phrases)`
2. Apply tokenization if necessary to break multi-word phrases into individual words.
3.  Pre-processed list of key phrases ready for mapping
Step III: Exact and Synonym-based Matching
1. FOR each key phrase `P` in `processed_key_phrases` DO:
    a. Perform **exact match**:
    i. IF `P` exists in the SNOMED-CT database as a preferred term, THEN:
      Assign the corresponding SNOMED-CT code to `P`.
      Example: `code = snomed_ct.lookup(P)`
b. IF no exact match is found, perform **synonym match**:
i. Search SNOMED-CT for any synonyms of `P`.
ii. IF a synonym match is found, THEN:
      Assign the SNOMED-CT code corresponding to the matched synonym.
      Example: `code = snomed_ct.lookup_by_synonym(P)`
2. Key phrases mapped to SNOMED-CT codes or flagged for further processing
Step IV: Fuzzy Matching and Ontology-based Expansion
1. IF no exact or synonym match is found for `P`, perform **fuzzy matching**:
a. Use fuzzy string matching techniques (e.g., Levenshtein distance or cosine similarity).
b. Find the closest matching SNOMED-CT term based on string similarity:
    Example: `closest_match = fuzzy_match(P, snomed_ct)`
i. IF the similarity score is above a threshold `T` (e.g., 0.8), THEN:
      Assign the SNOMED-CT code of the closest match.
```

ii. ELSE:

Flag the phrase for manual review.

2. Use ontology-based expansion for phrases that could represent broader concepts:

a. Identify potential parents or related concepts using the SNOMED-CT hierarchy.

b. Expand `P` by looking for more general terms that match in SNOMED-CT.

3. Fuzzy matched or expanded key phrases with SNOMED-CT codes

Step V: Context-based Disambiguation

1. Handle phrases that map to multiple SNOMED-CT codes (ambiguous matches):

a. Use the surrounding context of `P` (e.g., nearby words or the overall complaint) to disambiguate between potential codes.

b. Apply a disambiguation rule based on the type of phrase:

i. IF the phrase is a symptom, prefer SNOMED-CT codes related to symptoms.

ii. IF the phrase refers to an organ, prefer organ-related SNOMED-CT codes.

c. Use rule-based models trained on similar data for context-based disambiguation.

2. Unambiguous mappings of key phrases to SNOMED-CT codes

Step VI: Storing or Outputting Mapped Results

1. Store the mapped results:

a. Save each key phrase with its corresponding SNOMED-CT code in a structured format (e.g., CSV, JSON).

Example: `save_to_csv("snomed_ct_mapped_phrases.csv", mapped_phrases)`

b. Insert the mapped results into a database for further analysis or integration with clinical systems.

Example: `insert_into_db("clinical_db", mapped_phrases)`

2. Mapped key phrases with corresponding SNOMED-CT codes saved

Conclusion

Standardizing medical records ensures consistency in documentation. However, many Marathi medical terms are not yet included in existing ontologies, making accurate mapping challenging. Developing a comprehensive database requires significant domain expertise and effort.

4. Ontology Mapping with Named Entity Recognition (NER)

Named Entity Recognition (NER) is an **advanced NLP technique** that identifies key **medical entities** (symptoms, conditions, body parts) in text.

▪ Algorithm 7: NER + Ontology Mapping for Medical Phrase Extraction

Input: Chief complaints in Marathi (raw text), SNOMED-CT ontology database

Output: Extracted and mapped medical entities with corresponding ontology codes

Step I: Pre-process the Input Text

1. Clean and normalize the input text.

a. Remove unnecessary punctuation, special characters, and non-Marathi words using regular expressions.

b. Tokenize the text into sentences or words as required.

c. Perform stemming or lemmatization to standardize word forms.

2. Pre-processed and tokenized text ready for NER processing

Step II: Named Entity Recognition (NER)

1. Use an NER model (either rule-based or ML-based) to identify and classify entities such as symptoms, conditions, medications, and organs.

a. Load the trained NER model for medical domain entities in Marathi.

Example: `ner_model = load_model("marathi_medical_ner_model")`

b. Run the NER model on the input text to extract entities and their types (e.g., symptom, condition).

Example: `ner_results = ner_model.recognize_entities(tokens)`

c. Collect the extracted entities and their types.

```
entities = []
FOR each entity E in ner_resultsDO:
  Add E to `entities`
```

2. List of recognized entities with types (symptoms, organs, conditions, etc.)

Step III: Pre-load SNOMED-CT Ontology

1. Load the SNOMED-CT ontology or any other medical ontology that includes symptoms, conditions, medications, and anatomical organs.

a. Import SNOMED-CT concepts and related terms such as synonyms.

Example: `snomed_ct = load_snomed("snomed_ct_ontology.json")`

b. Set up an efficient data structure (e.g., a hash map or trie) for fast lookup of SNOMED-CT concepts.

2. SNOMED-CT loaded and structured for fast matching with recognized entities

Step IV: Map NER Entities to SNOMED-CT Codes

1. FOR each recognized entity `E` in `entities` DO:

a. Exact Match:

i. IF `E` matches a SNOMED-CT concept or preferred term, THEN:

Assign the corresponding SNOMED-CT code to `E`.

Example: `code = snomed_ct.lookup(E.text)`

b. Synonym Match:

i. IF no exact match, search for any SNOMED-CT synonyms of `E`.

ii. IF a synonym is found, assign the corresponding SNOMED-CT code.

Example: `code = snomed_ct.lookup_by_synonym(E.text)`

c. Fuzzy Matching (if no exact or synonym match):

i. Use fuzzy matching algorithms (e.g., Levenshtein distance) to find the closest matching SNOMED-CT concept.

Example: `closest_match = fuzzy_match(E.text, snomed_ct)`

ii. IF the similarity score is above a threshold `T`, assign the SNOMED-CT code of the closest match.

d. Store the results:

```
mapped_entities.append({
      "entity": E.text,
      "type": E.type,
      "snomed_ct_code": code
   })
```

2. List of recognized entities mapped to SNOMED-CT codes

Step V: Context-based Validation and Disambiguation

1. IF an entity `E` has multiple SNOMED-CT code matches, perform context-based disambiguation:

a. Use the surrounding context of the entity to resolve ambiguities.

Example: IF `E` is a symptom but maps to both an organ and a symptom code, prefer the symptom code based on surrounding words.

b. Apply specific disambiguation rules based on the entity type:

- IF the entity is a condition, prefer codes related to diseases or medical conditions.

- IF the entity is an organ, map it to anatomical codes.

c. Optionally, use a rule-based system to classify ambiguous entities.

2. Disambiguated and validated mappings of NER entities to SNOMED-CT codes

Step VI: Store and Output the Final Mappings

1. Store the final list of mapped entities and SNOMED-CT codes:

a. Save the results to a structured format like CSV or JSON for further analysis.

Example: `save_to_csv("mapped_ner_snomed_ct.csv", mapped_entities)`

b. Alternatively, insert the mappings into a database for integration with clinical systems.

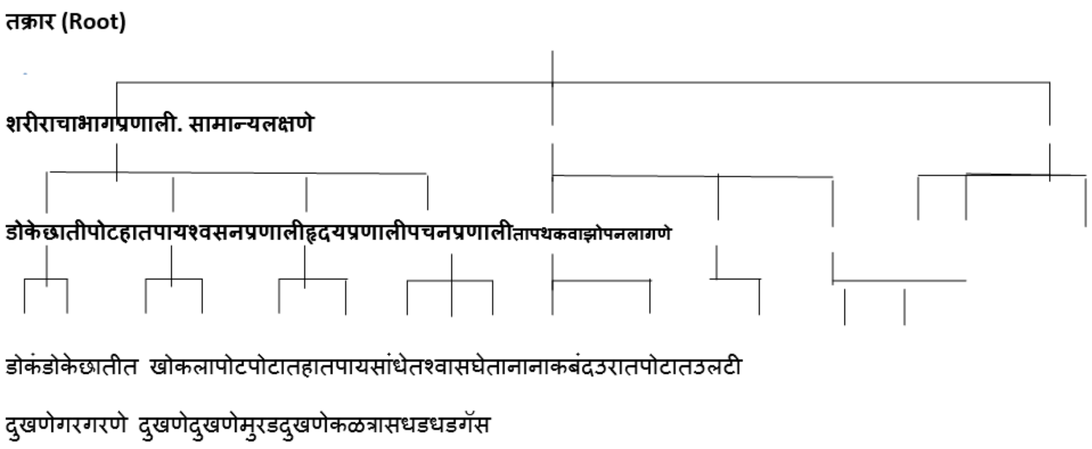
Example: `insert_into_db("clinical_db", mapped_entities)`

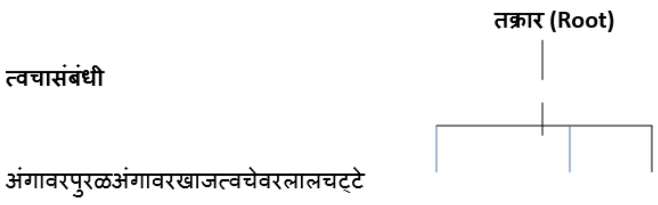
2. Final mapped entities with SNOMED-CT codes saved in structured format

Conclusion

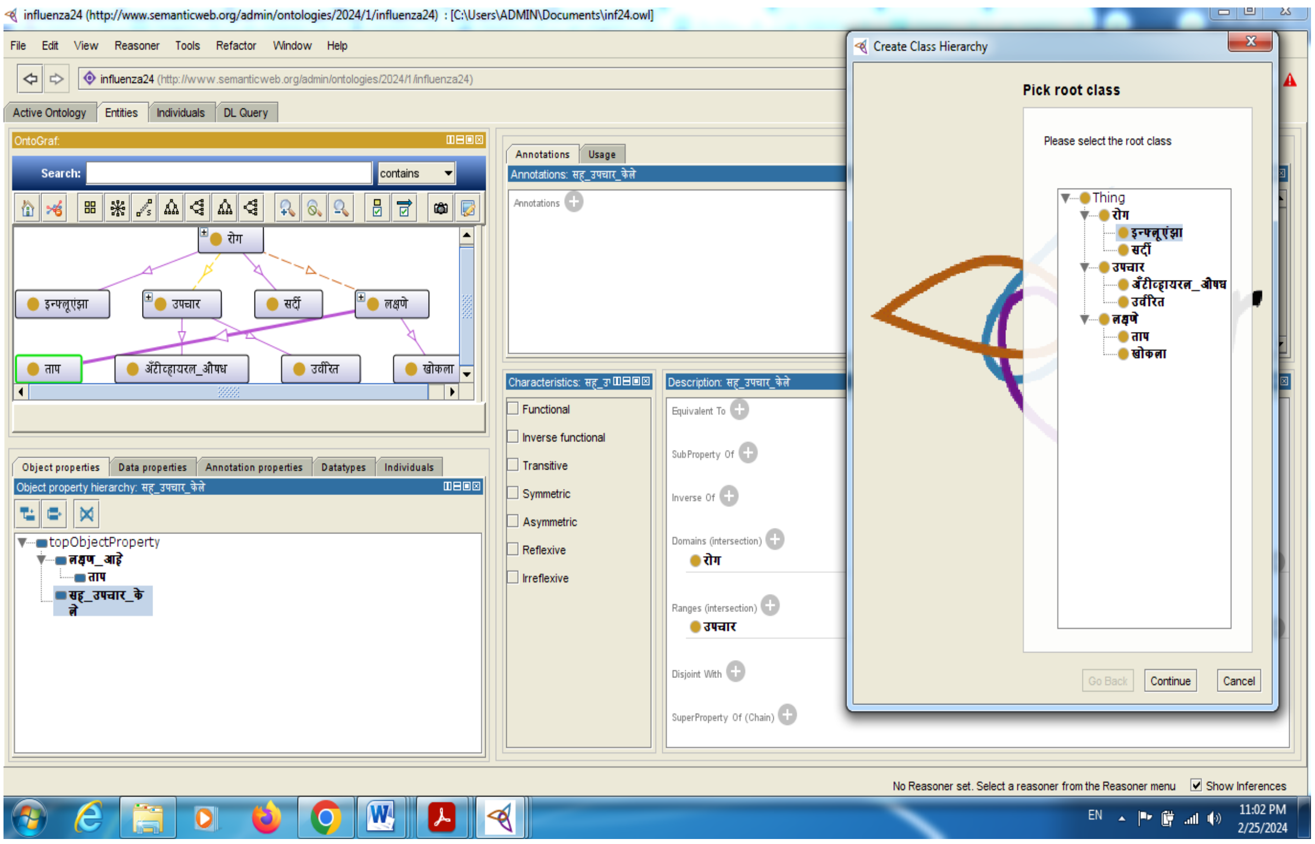
Ensuring standardization in medical terminology helps maintain consistency in records but requires extensive domain expertise. While it reduces ambiguity in medical terms, many Marathi medical terms are not yet included in SNOMED CT, posing a challenge for accurate mapping. Additionally, interoperability across healthcare systems is improved through standardized terminology; however, developing a comprehensive Marathi medical ontology remains a difficult and time-consuming task.

4. ONTOLOGY STRUCTURE FOR SAMPLE PATIENT COMPLAINTS.


तक्रार (Root)
शरीराचाभागप्रणाली. सामान्यलक्षणे
डोकेछातीपोटहातपायश्वसनप्रणालीहृदयप्रणालीपचनप्रणालीतापथकवाझोपनलागणे
डोकंडोकेछातीत खोकलापोटपोटातहातपायसांधेतश्वासघेतानानाकबंदउरातपोटातउलटी
दुखणेगरगरणे दुखणेदुखणेमुरडदुखणेकळत्रासधडधडगॅस



Here is a sample screen shot showing some key concepts related to flu disease in Protégé



Level 0 (Root): The root node of the ontology is "तक्रार" (Complaint).

Level 1: Branches out into major categories such as "शरीराचाभाग" (Body Parts), "प्रणाली" (Systems), "सामान्यलक्षणे" (General Symptoms), and "त्वचासंबंधी" (Skin-related).

To create ontology, define your domain and key concepts, and then use Protégé to add classes, properties, and individuals, saving your work regularly. Validate your ontology with a reasoner to check for inconsistencies.

The most effective approach is combining Ontology Mapping with Named Entity Recognition (NER), as it ensures accurate and scalable translations of medical terms.

5. RESULTS

5.1 Ontology Mapping Result:

Marathi Complaint	English Term	SNOMED CT Code	SNOMED CT Term
माझ्या छातीत दुखत आहे	Chest pain	29857009	Chest pain
माझ्या पाठीला वेदना आहेत	Back pain	279039007	Back pain
माझ्या डोक्यात दुखत आहे	Headache	25064002	Headache
माझा ताप येतो आहे	Fever	386661006	Fever
माझे पोट दुखत आहे	Abdominal pain	21522001	Abdominal pain
माझा खोकला आहे	Cough	49727002	Cough

5.2 The comparative chart showing precision, recall, F1 score, and accuracy for different NLP techniques.

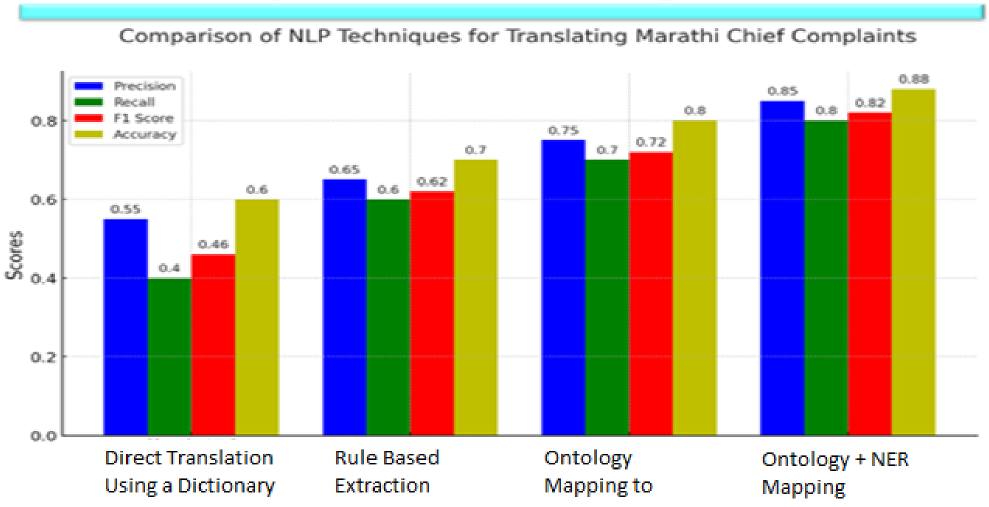
Technique	Accuracy (%)	Precision	Recall	F1Score	Advantages	Limitations
Direct Translation Using a Dictionary	0.60	0.55	0.46	0.4	Translating complaints helps doctors, nurses, and specialists from different regions collaborate more effectively.	Literal translation may leadto misinterpretation. Marathi expressions or metaphors used to describe symptoms might be mistranslated, affecting diagnosis.
Rule-Based Extraction	0.70	0.65	0.60	0.62	For well-defined, frequent patterns, rule-based systems can be highly accurate and precise, ensuring that common symptoms are consistently identified and translated correctly.	Rule-based systems can struggle with variations in language. Patients may express the same symptom in many different ways, but if the phrasing doesn't match the predefined rules exactly, the system may fail to recognize or translate the complaint correctly.
Ontology Mapping	0.80	0.75	0.70	0.72	Mapping to standardized medical codes enhances clinical decision support systems (CDSS). For instance, SNOMED CT's hierarchical structure allows for better symptom correlation and pattern recognition, which can help in diagnostics, treatment options, and clinical outcomes.	Both SNOMED CT and ICD-10 are extensive and detailed, making the mapping process complex. Accurately aligning patient complaints expressed in Marathi with the appropriate codes can be challenging, particularly for idiomatic or vague symptoms.
NER + Ontology Mapping	0.88	0.85	0.80	0.82	By combining NER with ontology mapping, patient complaints in regional languages (e.g., Marathi) can be translated into standard codes, making them interoperable across different healthcare platforms and regions. This allows patient records to be easily shared	NER systems might miss certain entities, especially when dealing with rare symptoms or conditions that are not commonly mentioned in the training data. Misidentified or missed entities can lead to incomplete or incorrect mapping during the ontology mapping process.

5.3. Comparative Analysis of Approaches or Pros & Cons of Each Method

Method	Strengths	Weaknesses
Direct Translation	Simple, quick	Lacks context, inaccurate for informal speech
Rule-Based Extraction	Effective for structured text	Labor-intensive, inflexible
Ontology Mapping	Ensures standardization, reduces ambiguity	Requires domain expertise, lacks full Marathi coverage
Ontology Mapping + NER	Scalable, accurate, adaptable	Needs large training data, high computational cost

5.4. Graph

❑ The comparative chart showing precision, recall, F1 score, and accuracy for different NLP techniques.



6. CONCLUSION

The most effective method is a combination of Named Entity Recognition (NER) and Ontology Mapping, as it offers the highest accuracy and can handle diverse language variations. While a word dictionary is quick and simple, it often misses context and struggles with slang. Rule-based extraction works well for structured text but lacks flexibility and is difficult to maintain. Ontology mapping helps standardize medical terms but requires extensive multilingual databases. In contrast, NER combined with ontology mapping leverages AI for improved accuracy, though it requires a large amount of training data for optimal performance.

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