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PAPER

A Novel Ontology-Based Approach for Analyzing Patient Sentiment Regarding Chronic Diseases

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ABSTRACT

Sentiment analysis (SA) plays a central role in understanding the multidimensional nature of comments on social media platforms like YouTube, Twitter, Facebook, and health forums. This article presents a multi-aspect, multi-sentiment annotation of chronic disease-related comments, highlighting the importance of connecting aspects, such as disease category and treatment, with corresponding sentiments (positive, negative, and neutral). The integration of ontologies enhances semantic consistency, enabling a comprehensive understanding of user experiences related to chronic diseases. The purpose of this paper is to bridge the gap between unstructured patient-generated content and actionable insights for healthcare professionals. A structured approach employing two ontologies—one for chronic disease aspects and another for sentiment classification—enables the linking of disease-related comments with associated emotions, supporting comprehensive SA. A multi-label classification model is trained to simultaneously predict multiple aspects and sentiments within a single comment, addressing the native complexities of sentiment expression. The article concludes with an evaluation of the model's predictions against real-world annotated data to assess its effectiveness. Our approach achieves promising results, demonstrating its ability to accurately link comments to their corresponding aspects and sentiments.

KEYWORDS

sentiment analysis (SA), ontology, multi-aspect, chronic disease, machine learning (ML)

1 INTRODUCTION

In our digital world, social media platforms have become a crucial source of extensive data due to the exponential growth in their use. Social media users freely share detailed aspects of their lives, ranging from political leanings and emotional states to health updates. This wealth of information has been applied in diverse areas, such as product marketing, political campaigning, tourism, healthcare, renewable energy, and various other sectors through the use of social media analysis.

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Sentiment analysis (SA) in chronic disease involves studying text data like patient reviews, forum discussions, or social media posts. It helps understand feelings and opinions about continuous health issues such as diabetes, hypertension, cancer, or depression [1, 2, 3, 4].

Traditional SA, using machine learning (ML) and deep learning, categorizes text sentiments into positive, negative, or neutral groups without always capturing the complex nuances of chronic diseases. ML-based SA usually involves algorithms trained on labeled datasets to recognize patterns and sort emotions. Standard methods use feature engineering, sentiment dictionaries, or statistical models such as support vector machines (SVM) or Naive Bayes for sentiment classification and deep learning techniques such as recurrent neural networks (RNN), convolutional neural networks (CNN), or long short-term memory (LSTM).

Integrating ontology into chronic disease SA offers significant advantages. By combining traditional SA with structured information from the ontology, we can contextualize the sentiments expressed in online discussions with precise medical data. This enables a deeper understanding of the feelings expressed by patients about their health conditions.

This paper introduces a multi-aspect, multi-sentiment annotation of comments related to chronic diseases, emphasizing the importance of linking specific aspects, such as disease category and treatment, with corresponding sentiments. An annotated dataset captures these intertwined aspects and sentiments (sentiment type and category). The motivation for this research lies in addressing the limitations of traditional SA methods in capturing the complexity of medical language. By leveraging ontologies, it aims to establish a structured framework for accurately understanding patient experiences. This work is driven by the need to advance semantic analysis techniques in the context of chronic diseases.

The study develops a dual ontology approach—one for chronic diseases and another for SA—designed to connect disease-related comments with emotional expressions, providing a structured basis for detailed sentiment analysis.

A multi-label classification model is trained to predict various aspects and sentiments within individual comments, addressing the complexity of SA in diverse health-related contexts. The model's effectiveness is assessed by comparing its predictions with real-world annotated data. This methodology offers a comprehensive approach for uncovering insights into patients' concerns, perspectives, and emotions, equipping healthcare professionals with valuable information to enhance personalized treatment and patient care.

The paper is organized as follows: Section 2 reviews related works on SA in general, with a particular focus on ontology-based SA. Section 3 describes our proposed approach. Section 4 details the classification models and performance measurements. Section 5 presents the experimental results and discussion. Finally, Section 6 concludes the paper and outlines future work.

2 RELATED WORKS

Ontologies are becoming increasingly popular in a variety of sectors, including web technologies, data integration, and, more recently, healthcare. They play an essential role in the creation of knowledge structures, helping to establish a common shared vocabulary in a specific domain such as chronic diseases. In the healthcare context, ontologies are particularly useful for managing and organizing information on treatments, medical protocols, and patient data. They help harmonize the terminology used in the healthcare sector, promoting better communication between healthcare professionals and the various IT applications. Implementing this strategy enables a more comprehensive understanding of healthcare data, which is crucial for areas such as ontology-based SA. In order to measure the feelings of patients with chronic illnesses, we use opinion or SA, which makes it possible to process large quantities of detailed, cost-effective data. The internet, including social media platforms, blogs, online reviews, and websites, generates a wealth of information about chronic diseases, particularly the symptoms and treatments described in patient comments. So, these online opinions of people with chronic diseases play an important role in influencing authors, healthcare providers, and decision-makers, underscoring the need for access to unstructured data.

2.1 Related work to sentiment analysis

Machine learning and deep learning have shown great potential in various domains, particularly in healthcare for predicting and diagnosing diseases [5, 6, 7]. Similarly, SA—or opinion mining—applies these methods to understand opinions by analyzing text at various levels: document-level [8, 9, 10], sentence-level [11], and aspect-level [12].

The aim of this study [13] was to examine people's perceptions and attitudes towards breast cancer, in particular those relating to physical activity, on Twitter. To do this, they began by identifying and collecting tweets about breast cancer. They then used topic modeling and SA techniques to identify topics of discussion and assess Twitter users' perceptions and emotions towards breast cancer. In addition, they studied two different deep learning algorithms: CNNs and LSTMs.

This study [14] investigated the dynamics of feelings within online health communities, focusing specifically on the narratives of breast cancer patients. A DL model was used to analyze variation in sentiment and determine changes in emotions and coping mechanisms during treatment. The study revealed the effectiveness of the BiLSTM model with sentiment integration features, achieving an impressive F1 score of 91.9%.

This paper [15] presents a new method for analyzing Moroccan users' Twitter sentiments during the COVID-19 crisis, running from March 2020 to the end of August 2020. The approach is based on innovative collaborative filtering using four new tweet features, combining the Python library TextBlob and a SenticNet dictionary-based approach. Results show that this method outperforms existing classification approaches, achieving an accuracy of 86%. Applying this method to Moroccan tweets on COVID-19 reveals that the majority of content posted on Twitter on this topic is negative.

Alexander et al. [16] demonstrated the accuracy of sentiment classification and the effectiveness of topic modelling in patient comments in England. Their study used NLP and ML techniques to develop an innovative text analysis tool. In three iterative phases, they analyzed sentiment, identified themes, and created an interactive web-based data visualization application to make the results easily accessible to the general public.

Clark et al. [17] discovered that sharing experiences through English tweets had a positive effect on the treatment and awareness of breast cancer patients. These findings highlight the role of social media as a means for patients to openly discuss their medical needs and treatment journey.

In this study [18], they examined the feelings of various cancer patients by analyzing tweets from different online support communities. They developed a distributed framework using text mining and ML strategies, including a LSTM, for fast and efficient SA. The results showed a majority of positive opinions about the disease, although some negative and neutral opinions were also expressed, validating the effectiveness of our approach compared to traditional methods.

This study [19] presents an analysis of individuals' reactions to colorectal cancer to predict the future of this disease. The dataset utilized was obtained from Twitter, and various deep learning models (LSTM, GRU, and CNN) were assessed. The findings underscore the superiority of the GRU model in terms of both accuracy and stability when compared to the LSTM and CNN models.

This study [20] explored SA of Indonesian texts using the transfer learning technique with the IndoBERT pre-trained model. The methodology adopted included data collection from the Google Play website, manual labeling (based on a dataset of 9,310 reviews, with each review labeled as positive or negative), data preparation, division into training, validation, and test sets, and the development and fitting of a classification model based on IndoBERT. The training process involved the use of 10 epochs with the Adam optimizer and a learning rate of 1e-6. Evaluation of the model revealed impressive results, with high accuracy of 96%, an F1 score of 95%, recall of 96%, and precision of 95%.

This research [21] presents a novel methodology for SA on microblogs, focusing on suicide prediction. The study introduces the concept of structure similarity in social networks and incorporates social and topic context into the analysis to provide a more comprehensive understanding of user sentiment. By modeling semantic relationships and applying Laplacian regularization to the SA model, the methodology aims to improve the accuracy and reliability of sentiment classification on microblogs. Experimental results demonstrate that the proposed model outperforms baseline methods, with an accuracy of 0.821 for dataset 1 and 0.834 for dataset 2.

This study [22] uses supervised ML models to assess sentiments related to depression. It employs two classification approaches: a numerical classifier and a three-way classifier based on tweet polarity (negative, positive, neutral). The research utilizes Twitter datasets on depression and SA from Kaggle. Pre-processing steps include removing URLs, stop words, and numbers, as well as incorporating sentiment columns. The results show that the logistic regression model achieved the highest accuracy of 96.3% in depression SA, closely followed by the SVM model with 96.2%. The XGB Classifier and Random Forest models also performed effectively, with accuracy rates of 96.1% and 95.2%, respectively.

The study [23] investigates the application of ML and natural language processing techniques to analyze posts related to depression and suicide on Reddit. Data was gathered from the "SuicideWatch" subreddit, processed, and used to train models including SVM, logistic regression, Naïve Bayes, and random forest. The models achieved the following accuracies: 77.29% for logistic regression, 74.35% for Naïve Bayes, 77.12% for SVM, and 77.298% for random forest.

2.2 Literature study in ontology-based sentiment

In this article [24], they explained how ontologies can be used to predict the presence of COVID-19 based on symptoms. They integrated ontology and ML by implementing the rules of the decision tree algorithm in the ontology reasoner. In addition, they evaluated the results by comparing them with various ML categories used to make predictions. The findings are evaluated using performance measures obtained from the confusion matrix, including F-measure, accuracy, precision, and recall. According to the results, the ontology outperformed all ML algorithms in terms of accuracy, achieving a score of 97.4%.

The paper [25] presents an approach to aspect-based SA that is enhanced by ontology and focuses on improving sentiment classification in online reviews. The study utilized restaurant review data from Task 5 of SemEval 2016, comprising training data with 350 reviews and 1992 sentences and test data with 90 reviews and 676 sentences. The ontology was structured into two main classes—Mention and Sentiment—with subclasses representing specific aspects and properties related to entities in the domain. The proposed algorithm combined a bag-of-words model, external dictionaries, and the ontology to enhance aspect sentiment classification. The results of these ontology-enhanced methods showed significantly better performance in aspect sentiment classification, with higher F1 scores compared to methods without ontology features.

The proposed approach in the study [26] utilizes an Emotion Ontology model and Semantic Web technologies for SA of COVID-19-related tweets, aiming to extract a wide range of human emotions expressed during the pandemic. The Emotion Ontology model demonstrates high precision and recall values for classifying emotions, outperforming existing models and providing valuable insights into public sentiment during global health crises.

The objective of this proposed work [27] is to analyze the sentiments of users in a particular Facebook group regarding various schools and create a recommendation system using their reviews. To model the school's knowledge base, they created a school ontology that allows for the extraction of relevant opinions and the calculation of sentiment polarity.

The researchers [28] presented a framework to analyze sentiments expressed by social media users through the use of domain ontology, ML, and lexicon-based techniques. They used community detection analysis to comprehend the structure of groups formed in the case studied. They employ domain ontology to filter data, which is then followed by a preprocessing phase to cleanse the text in their pipeline. Next, they utilize algorithms that use lexicon and ML to identify and calculate sentiment scores and then display the results in different formats on their analytics console.

Compared to current approaches, which primarily rely on generic ML methods, deep learning algorithms, or lexicon-based techniques, and are often unable to capture the subtle relationships between patient sentiments and disease-specific aspects, ontologies, although widely used in other domains to enhance semantic consistency and optimize data analysis, have remained largely unexplored in the context of SA for chronic diseases. This research aims to address this gap by introducing an ontology-based framework designed to complement existing methods, improve accuracy, and provide deeper insights into SA within the context of chronic diseases.

3 OUR APPROACH

Building an ontology using "protégé" [29] to analyze the feelings associated with chronic diseases requires the creation of a structured framework to define the relationships and connections between the different aspects, feelings, and entities associated with these diseases.

The proposed approach for our research problem is shown in Figure 1.

3.1 Collect data

Collecting comments from various online platforms such as YouTube, Facebook, Twitter, and RSS feeds is a crucial part of our methodology for analyzing user experiences related to chronic diseases. These sources provide a diverse range of comments, ratings, and other forms of user feedback, ensuring a variety of viewpoints and experiences. The collected data is centralized into a single dataset for in-depth analysis.

Analyzing the feelings associated with chronic illnesses, especially in the context of user experience, is a complex research topic primarily due to the lack of labeled data necessary for accurate emotion classification. To address this, we create a reference dataset by annotating the collected comments for various aspects such as chronic diseases, treatments, and categories of treatment, along with the corresponding positive, negative, or neutral feelings. For negative sentiments, we classify emotions such as sadness, stress, anxiety, despair, fear, frustration, hopelessness, isolation, and melancholy. Positive emotions include encouragement, gratitude, happiness, hope, joy, optimism, and confidence. Neutral sentiments are categorized as astonishment, confusion, indifference, and surprise.

3.2 Pre-processing

The pre-processing method involves the following steps to create structured corpus data that facilitates the extraction of features related to chronic diseases and opinion words. Furthermore, these actions are utilized to clean the corpus data and prepare it for word embedding techniques.

- Stop-word removing and cleaning: Eliminate any stop words like 'are,' 'is,' 'am,' and articles 'a, an, the,' etc. It's important to delete these words as they don't emphasize any emotions, to reduce the noise from the comments.
- Tokenization: involves breaking comments down into terms or tokens by eliminating whitespace, commas, and other symbols. In our work, this step is crucial as we focus on individual words to identify the aspects.
- Eliminating URLs is necessary because it has no impact on classification.
- Stemming and lemmatization: Stemming involves transforming words into their root form, such as changing "friendly" to "friend," while lemmatization involves reducing words to their base form, such as transforming "spoken" to "speak."
- Eliminating special characters and punctuation: Special characters and punctuation can introduce unwanted noise to the data, contributing little to no value in the analysis. Their removal aids in creating cleaner and more easily analyzable data.

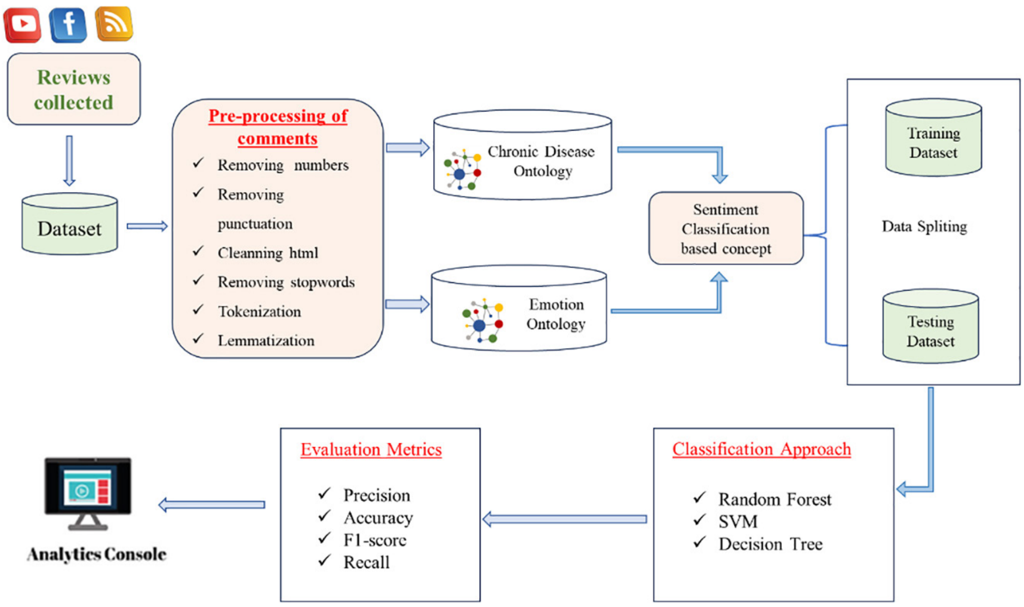

Fig. 1. Flowchart of our proposed methodology for aspect-level sentiment analysis enhanced by ontology

3.3 Integration of ontologies for semantic enrichment

To enhance the interpretability and relevance of the predictions, we integrated domain-specific ontologies after the preprocessing stage. This methodology ensures that the model's outputs are semantically consistent and aligned with structured domain knowledge. We implemented a structured ontology specifically adapted to chronic diseases to map the different aspects of diseases, such as types, treatments, and the links between them. At the same time, an ontology dedicated to feelings will be created to represent the different nuances of emotions expressed in comments, including categories like positive, negative, and neutral. Based on both ontologies, we can establish links between specific aspects of diseases and the feelings expressed about them.

Ontology of chronic disease. Our purpose in developing this ontology is to create an organized vocabulary for describing concepts related to diseases and their treatments, with a particular focus on conditions like diabetes, high blood pressure, and depression. We center our ontology on categorizing diseases into classes and subcategories, encompassing essential health areas such as monitoring, lifestyle, and medication management. For example, subclasses such as Blood_Pressure_Monitoring, Diabete, and Depression offer a structured breakdown, allowing us to capture the interrelations between different health conditions and their treatment pathways.

Each disease category includes attributes relevant to treatment options. As shown in Figure 2, our hierarchical ontology illustrates various disease types and their subcategories, organized to reflect the relationships among classes such as high blood pressure and its associated subclasses, blood pressure monitoring and high blood pressure medications.

In a similar structure, we define specific treatment subclasses, such as diabete-medications, high-blood pressure-medications, and depression-medications. The diabete class, for instance, connects to Blood Sugar Monitoring through the property hasMonitoring_Diabete and links to Diabete_Medications via isTreatment_of_Diabete. We apply the same relational approach to other conditions, creating a comprehensive and interconnected ontology that systematically organizes medical concepts for better healthcare application and analysis.

Ontology of emotion. Using the "Protégé" ontology modeling environment [29], we developed an ontology focused on emotions associated with chronic diseases, especially as expressed on social networks. Our goal was to analyze patient behavior by categorizing their emotional responses to various chronic health conditions. The structure of our ontology shown in Figure 3 begins with the Emotion class, which we divided into Positive Emotions, Negative Emotions, and Neutral Emotions.

We further organized each emotion type into specific feelings. For instance, Positive Emotions includes classes such as Joy, Gratitude, and Optimism, while Negative Emotions encompasses Anger, Anxiety, Despair, and Frustration. The Neutral Emotions subclass contains categories such as indifference, confusion, and surprise. Each emotion is associated with properties such as hasCause and experiencedB..., which we used to link emotions to potential triggers or situations that might elicit them. Additionally, we defined the hasIntensity property to quantify the strength of each emotion, allowing us to capture the intensity of patients' feelings.

To construct this ontology, we analyzed patient comments and discussions on chronic health conditions to identify common emotional keywords. Through this structured approach, we created a framework to systematically capture and examine patients' emotional responses to chronic diseases, providing insights into the impact of chronic illness on mental and emotional well-being as reflected in social network discussions.

Mapping process. Using these ontologies, we established semantic links between disease-specific aspects and the corresponding feelings expressed about them:

- **Disease ontology mapping:** Predictions related to diseases (e.g., "Diabetes") were mapped to specific ontology classes (e.g., #Diabete). Subclasses such as treatments (e.g., #Diabete_Medications) and monitoring methods (e.g., #Blood_Sugar_Monitoring) were linked to their parent classes, providing hierarchical context. Unmapped predictions were labeled as "undefined" to ensure consistency.
- **Sentiment ontology mapping:** Predicted sentiments were matched directly to specific ontology classes. For instance, a prediction such as "Joy" was mapped to the class #Joy. These predictions were further contextualized within the ontology's hierarchy, linking them to broader categories such as #Positive_Emotions. This hierarchical alignment enabled both detailed and general analyses of sentiments.
- **Integration of both ontologies:** By leveraging both ontologies, we linked disease-specific aspects with the emotions expressed about them: For example, a prediction of "Diabetes" paired with a sentiment of "Stress" was mapped to #Diabete in the Disease Ontology and #Stress in the Sentiment Ontology, creating a connection between the chronic condition and the negative emotion expressed.

The Table 1 provides some examples of comments with a detailed analysis of various comments made by people discussing their state of health. Each comment is classified according to the disease, the specific subclass, and the sentiment expressed by the patient.

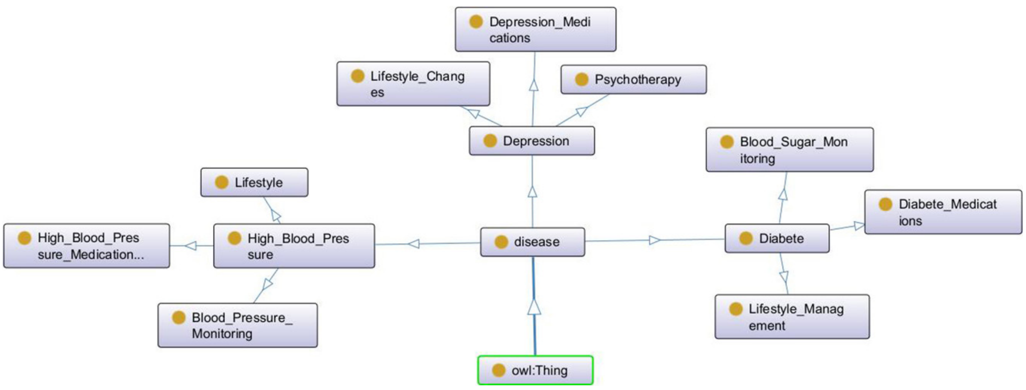

Fig. 2. Ontology chronic disease

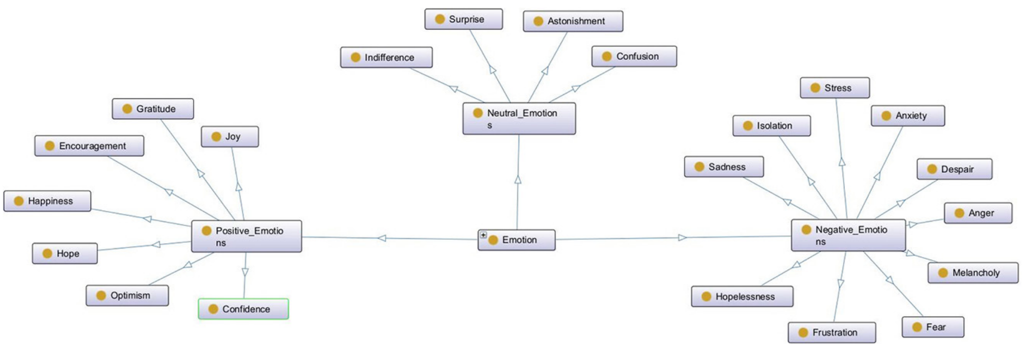

Fig. 3. Ontology emotion

Table 1. Examples of health-related comments with disease and sentiment classification

Comments	Disease Category	Treatment	Sentiment	Sentiment Category
This medication is amazing! After 3 days of being extremely sick, I started to feel amazing, I am now 1 month into it and am so happy all the time and have no depressive thoughts at all. It kind of blocks out any sad thoughts. Works perfectly for me.	Depression	Depression_ Medications	Joy	Positive_ Emotions
I have been this medicine for 4 weeks now. I started at 0.6 for a week then went up to 1.2 on the eighth day. Side effects the first couple weeks included nausea, sore back, headache, sour stomach, etc. though none of them were unbearable.	Diabetes	Diabetes_ Medications	Stress	Negative_ Emotions
I was put on Glipizide ER after having bad side effects from Metformin ER. Had the diarrhea with it. Have had no problems with Glipizide.	Diabetes	Diabetes_ Medications	Indifference	Neutral_ Emotions
"I started 10mg of Brintellix over a month ago for depression. No side effects or any issues, I feel great!"	Depression	Depression_ Medications	Happiness	Positive_ Emotions

4 CLASSIFICATION MODELS AND MEASUREMENT OF PERFORMANCE

Machine learning techniques are widely used in SA to classify opinions, emotions, and attitudes expressed in text data. However, a major challenge lies in accurately capturing the nuances and complexities of language, especially within specific domains such as healthcare. By incorporating ontologies, which provide a structured vocabulary and relationships between terms, ML models can better understand contextual meanings, improving the classification of sentiments related to targeted topics. This approach not only increases the precision of SA but also allows for a more refined categorization of emotions and attitudes, essential for applications where nuanced interpretation is critical, such as analyzing patient feedback in healthcare.

4.1 Machine learning

Various classification methods have been developed in the field of ML, utilizing different strategies to classify unlabeled data. Training data is often necessary for these classifiers. Random forest, decision tree, and SVM are just a few examples of ML classifiers that can be utilized. These approaches are categorized as supervised learning techniques because they rely on training data. It's important to acknowledge that effective training enhances a classifier's ability to make accurate future predictions.

Support vector machine. The primary goal of SVM [30] is to determine the optimal hyperplane to distinguish data points into distinct classes, typically positive and negative. In binary classification scenarios, SVM aims to locate a hyperplane that maximizes the margin between these classes. This margin signifies the distance between the hyperplane and the nearest data points from each class. Additionally, SVMs can address non-linearly separable data by employing kernel functions to transform it into linearly separable form within a higher-dimensional feature space.

Decision tree. Decision tree: is an essential tool in classification, functioning by progressively segmenting data into homogeneous subsets, aiding interpretation.

They offer flexibility in handling complex datasets and simplify decision visualization due to their tree-like structure. Decision trees come in two main types: classification trees for discrete decision variables and regression trees for continuous values.

Random forest. The random forest method [31] enhances prediction accuracy and model stability by combining multiple decision trees. It does this by training each tree on different random subsets of the training data and then aggregating their predictions. Random Forest introduces randomness in two main ways. First, at each decision node, it selects random feature subsets to determine splits, which minimizes overfitting and adds variation among the trees. Second, it uses bootstrap sampling, where each tree is trained on randomly selected subsets of the data with replacement, further diversifying the trees and lowering model variance. Random Forest is particularly effective for handling large and noisy datasets and provides insights into feature importance. It is widely used in ML for both classification and regression tasks.

4.2 Measurement of performance

The performance of the proposed technique is evaluated for all the data selected. To do this, we use four information retrieval parameters: accuracy, precision, recall and F-measure.

The accuracy metric is used to calculate the percentage of accurate predictions. This refers to the ratio between the number of correct predictions and the total number of input samples or observations, as displayed in equation 1.

$$\text{Accuracy} = \frac{True\,Positives + True\,Negatives}{True\,Positives + True\,Negatives + False\,Positives + False\,Negatives} \quad (1)$$

Precision is a key indicator for assessing whether a model's positive predictions are accurate, by calculating the percentage of positive instances correctly identified.

$$\text{Precision} = \frac{True\,Positives}{True\,Positives + False\,Positives} \quad (2)$$

The true positive rate, or Recall is a metric used for assessing the performance of a model, specifically its ability to correctly recognize all relevant instances of a class within a dataset.

$$\text{Recall} = \frac{True\,Positives}{True\,Positives + False\,Negatives} \quad (3)$$

The F1-score is an integrated metric that assesses a classifier's performance by combining both precision and recall. This metric optimally balances the classifier's accuracy in identifying positive instances and its effectiveness in covering all relevant instances. The F1-score can be calculated as follows:

$$\text{F1-score} = \frac{2 \cdot (precision * recall)}{precision + recall} \quad (4)$$

5 RESULTS

The results presented in the Table 2 and in Figure 4 demonstrate the performance of different ML models (random forest, decision tree, and SVM) combined with our approach (ontology) across four prediction tasks: disease category, treatment, sentiment, and sentiment category. The metrics used (accuracy, precision, recall, and F1-score) highlight how well the models perform in these tasks.

5.1 Disease category

The highest performance for disease category prediction is achieved using SVM, with an accuracy of 95.71% and an F1-score of 95.71%. Decision tree also performs well (accuracy: 95.26%, F1-score: 95.26%), closely followed by random forest (accuracy: 94.09%, F1-score: 94.59%).

5.2 Treatment

The SVM model again performs best for treatment prediction, with an accuracy of 94.93% and an F1-score of 94.80%, slightly outperforming decision tree (accuracy: 94.76%, F1-score: 94.55%). Random forest trails with an accuracy of 92.71% and an F1-score of 93.42%.

5.3 Sentiment

For sentiment prediction, Random forest achieves the best performance, with an accuracy of 86.21% and an F1-score of 86.22%. SVM follows closely (accuracy: 81.20%, F1-score: 81.24%), while decision tree lags significantly (accuracy: 67.21%, F1-score: 67.28%).

Table 2. Results

Ontology Concepts	Model	Accuracy	Precision	Recall	F1-Score
Disease category	Random Forest + Ontology mapping	94.09%	94.59%	94.64%	94.59%
Treatment		92.71%	93.42%	93.38%	93.42%
Sentiment		86.21%	86.22%	86.45%	86.22%
Sentiment category		84.18%	84.83%	85.86%	84.83%
Disease category	Decision Tree + Ontology mapping	95.26%	95.24%	95.26%	95.26%
Treatment		94.76%	94.51%	94.76%	94.55%
Sentiment		67.21%	67.68%	67.21%	67.28%
Sentiment category		80.54%	80.72%	80.54%	80.54%
Disease category	SVM + Ontology mapping	95.71%	95.80%	95.77%	95.71%
Treatment		94.93%	94.93%	94.93%	94.80%
Sentiment		81.20%	81.59%	81.20%	81.24%
Sentiment category		84.66%	84.97%	84.66%	84.76%

5.4 Sentiment category

Support vector machine outperforms the other models in sentiment category prediction, with an accuracy of 84.66% and an F1-score of 84.76%. Random forest shows competitive performance (accuracy: 84.18%, F1-score: 84.83%), whereas Decision tree has the lowest scores (accuracy: 80.54%, F1-score: 80.54%).

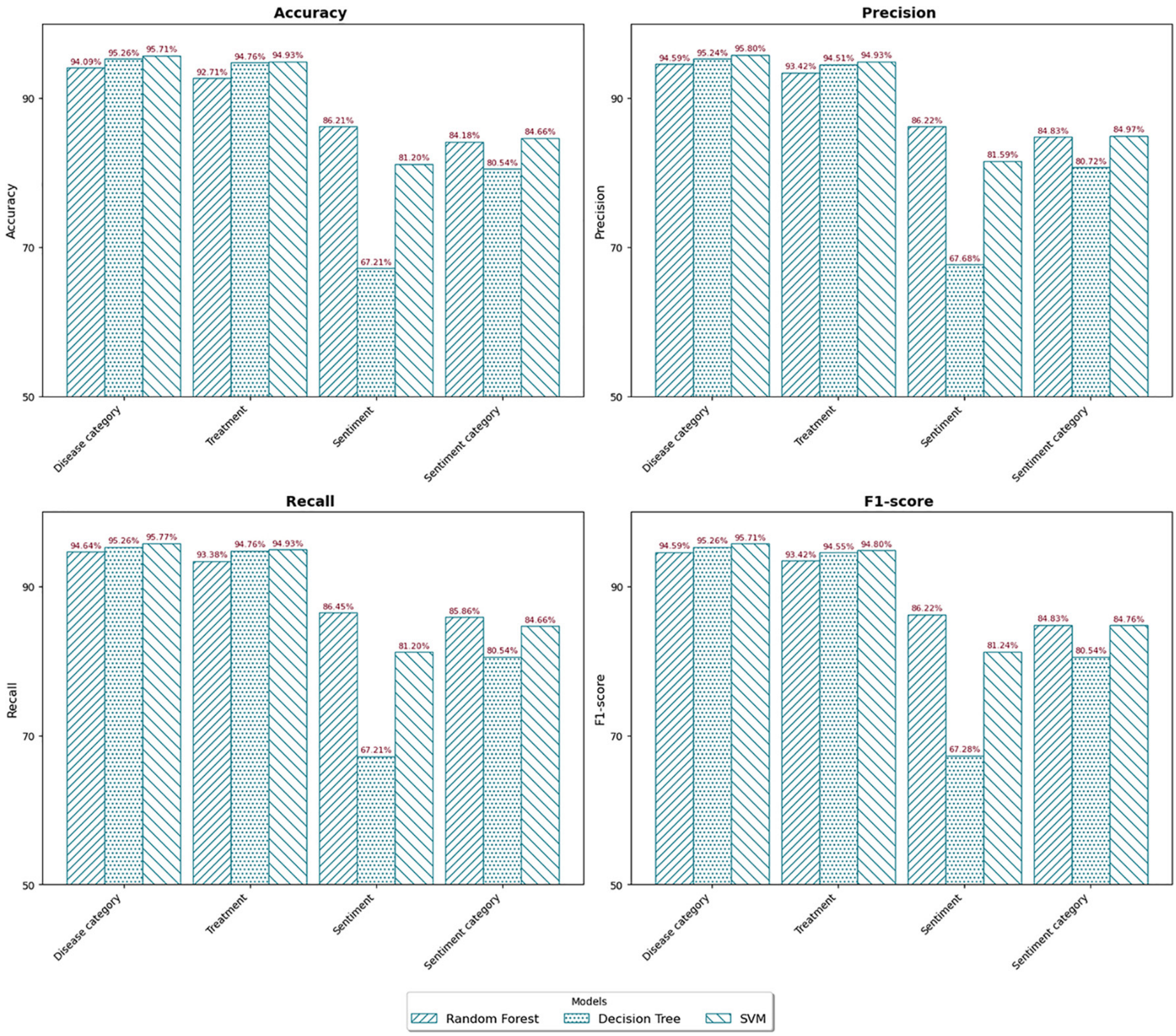

Fig. 4. Reports the evaluation metrics for classifier performance

6 DISCUSSION AND LIMITATIONS

6.1 Interpretation of the results

The interpretation of the results indicates that ontology mapping has a significant positive impact on the performance of all models across prediction tasks. The three models demonstrated strong results for disease category prediction, with SVM slightly ahead due to its ability to effectively handle non-linear relationships. In treatment prediction, SVM and decision tree performed best, suggesting that these models are particularly well-suited for this task when enriched with ontology-based features.

In sentiment prediction, random forest outperformed other models, showcasing its ability to capture complex relationships in textual data, especially when enhanced with ontology mapping. Finally, for sentiment category prediction, both SVM and random forest were effective, likely due to their capability to process the enriched features provided by the sentiment ontology. Overall, these results underscore the importance of ontology integration in improving model performance across diverse prediction tasks.

6.2 Limitations

This study faces some limitations that must be acknowledged. The annotated dataset focuses exclusively on chronic diseases, overlooking other significant health issues such as acute illnesses, infectious diseases, and mental health conditions. Additionally, the complexity of sentiment expression presents challenges, as patient sentiments are often ambiguous or involve mixed emotions, making it difficult to achieve complete accuracy. Finally, the reliance on patient-generated content introduces data quality issues, including noise, incomplete information, and biases, which can further impact the precision and reliability of the analysis.

7 CONCLUSION AND FUTURE WORK

This study demonstrates the effectiveness of integrating ontology mapping with ML models to enhance predictive accuracy and interpretability in various domains, including disease categorization, treatment prediction, and SA. The use of structured ontologies enriched the models with semantic knowledge, aligning predictions with domain-specific concepts and improving their generalization capabilities. The results show that SVM consistently performed best in structured tasks, such as disease and treatment predictions, while Random Forest excelled in sentiment-related tasks, particularly in handling complex textual data.

To build on the findings of this study and address its limitations, future research could expand the scope of ontologies to include a broader range of diseases, such as acute illnesses, infectious diseases, and mental health conditions, alongside treatments and sentiments. This would enhance the framework's adaptability and applicability to diverse healthcare domains. Additionally, generalizing the approach to areas like pharmaceuticals and public health campaigns could validate its versatility. Optimizing the model for real-time analysis would allow healthcare professionals to dynamically monitor patient feedback on social media. Furthermore, optimizing existing algorithms could further improve accuracy and efficiency, ensuring better performance across tasks. Finally, extending the framework to handle multilingual data would enable SA across various linguistic and cultural contexts, expanding its utility.

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