

Narrative Analysis of Natural Language Processing Applied to the Mental Health Monitoring System

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Abstract: The growing prevalence of mental health issues underscores the need for innovative and effective monitoring systems. Traditional approaches to mental health assessment often rely on self-reported data and clinical evaluations, which can be limited in scope and frequency. Recent advancements in machine learning offer promising alternatives for real-time, scalable, and objective mental health monitoring. Among these advancements, text-based analysis using sentiment analysis and emotion detection has emerged as a powerful tool for understanding and managing mental health. Despite significant progress in sentiment analysis, existing models frequently encounter limitations in addressing the complex and nuanced nature of emotional expression across diverse cultural contexts. Standard models often fail to capture the full spectrum of emotional experiences due to their limited cultural adaptability and inability to handle dynamic emotional states effectively. Natural Language Processing (NLP) refers to a collection of methods for identifying, reading, extracting and untimely transforming large collections of language. In this work, we aim to give an overview of how NLP has successfully been applied thus far in Mental Health Monitoring system.

We conduct a literature search on PubMed, Scopus Web of Science and Google Scholar for scientific articles published between 2007 and 2024. We use both quantitative and qualitative methods to screen papers and provide insights into the inclusion and exclusion criteria. We outline our approach for article selection and provide an overview of our findings. This is followed by a more detailed insight into selected article. Overall, 2000 articles were screened for the suitability of this review, where we review 69 articles in depth. Finally, we discuss future avenues of research and outline challenges in existing work.

Keywords: Natural language processing, Mental health Monitoring, Machine learning.

I. Introduction

The field of artificial intelligence (AI) research known as "natural language processing" aims to enable computers to comprehend spoken and written natural language in a manner similar to that of humans. To accomplish the aforementioned goal, one can use knowledge of statistics, machine learning, deep learning, and computational linguistics (rule-based modelling of human language) separately or in combination. The area of artificial intelligence known as "natural language processing" (NLP) is concerned with how computers and human language interact. It makes it feasible for computers to comprehend, interpret, and produce human language by allowing them to process and analyse vast volumes of natural language data. Information retrieval, sentiment analysis, and machine translation are just a few of the fields that heavily rely on NLP approaches.

A branch of artificial intelligence called machine learning (ML) enables computers to learn from their experiences and get better over time without explicit programming. Machine learning algorithms are essential to natural language processing (NLP) because they allow models to automatically discover linguistic patterns in vast amounts of data. NLP has undergone a revolution thanks to supervised learning, unsupervised learning, and deep learning techniques like neural networks, which have made it possible to do tasks like text classification, named entity identification, and question answering.

Significant progress has been made as a result of the convergence of NLP and ML, especially with the creation of models like BERT, GPT, and transformers that use massive datasets to produce and comprehend language at the cutting edge.

Use of NLP and Its Effect in the Real World

Numerous applications have emerged from the fusion of machine learning and natural language processing: Machine Translation: End-to-end neural translation systems, driven by encoder-decoder models and transformers, have supplanted early rule-based translation systems and achieved translation quality that is almost human-level for several languages.

Sentiment Analysis: NLP models can automatically categorize text sentiment through deep learning and transfer learning, which is helpful for customer feedback analysis, brand reputation management, and social media monitoring.

Chatbots and Conversational Agents: By combining natural language processing (NLP) and reinforcement learning, intelligent chatbots that can comprehend and produce dialogue that sounds human have been made possible. Examples of huge language models performing exceptionally well in these conversational tasks are systems such as Open Ai's Chat GPT.

Summarizing and Text creation: Document summarizing and text creation are now frequently accomplished using pre-trained transformer models. These tools support academics by condensing lengthy study papers or gleaning significant insights from vast amounts of text, in addition to aiding in the development of material.

Whilst there are a variety of surveys and literature reviews in NLP and its various subtasks, there is no review of NLP and text mining techniques used in the field of occupational and environmental exposure research. This review fills that gap by providing a

description of existing tools based on NLP and text mining techniques that have been applied in occupational and environmental exposure research. For this, we utilise a hybrid approach combining classical and automatic reviewing methods with Robot Analyst, which is a recently developed web-based software system that combines text mining and machine learning algorithms. Papers published in the PubMed, Scopus and WoS databases are screened and reviewed to answer the following research questions:

- What resources are used for this task?
- What are the most common NLP methods used?
- What are the main challenges and future directions of research?

II. Review Methodology

Three databases of scientific literature were searched for this literature review. We include peer-reviewed, full-length papers. Our search yielded 2000 items, of which 1000

were chosen for pre-screening following the elimination of duplicates. The selection procedure for this review is depicted in Figure 1, where we utilized the following search phrases for each search on the three platforms (PubMed, Scopus and Web of Science, and Google Scholar):

The pre-screening procedure was carried out in two stages. First, we used Robot Analyst to find 1000 complete papers in order to lessen the human workload. Robot Analyst is a free and open-source software program that uses machine learning and text mining techniques to classify and score references according to their applicability. Using an iterative classification method, the system bases its choices on each reference's abstract.

The titles and abstracts of those papers were then manually filtered using the inclusion and exclusion criteria listed below. Two occupational exposure specialists supplied the inclusion and exclusion criteria that were utilized to choose papers that were pertinent to occupational exposure research. We found 80 papers that particularly addressed natural language processing in the context of mental health based on these criteria. The complete publications were then examined for their applicability to text mining or NLP techniques and occupational exposure. After 100 copies of the complete papers were eventually obtained and thoroughly examined, 69 articles in all met our specified inclusion and exclusion criteria.

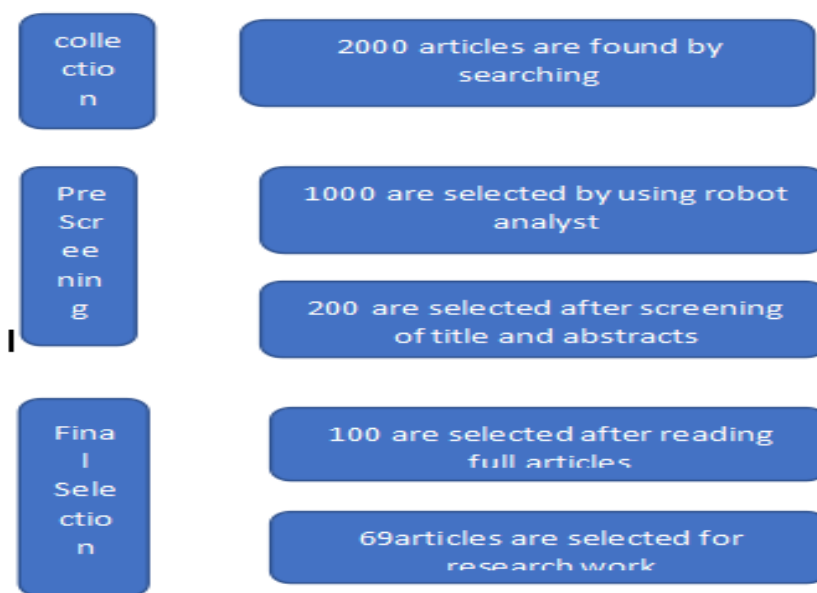


Figure 1: Review process

Related Works

With the dynamic nature of technology, effectively monitoring mental health of people has resulted in a variety of approaches. This review evaluates major studies, focusing on approaches and results. Text-based approaches for mental health monitoring leverage natural language processing (NLP) and machine learning to analyze written content for emotional and psychological insights. Early research sentiment analysis to gauge overall sentiment from text data, which has evolved to more sophisticated emotion detection techniques. One notable study, referenced as [1], proposed an algorithm aiming to monitor mental health based on textual data, guided by social media and forums.

The paper titled "**Predictive Analysis of Mental Health Conditions Using AdaBoost Algorithm**" focuses on the use of AdaBoost, a boosting algorithm, for predicting mental health conditions. The study demonstrates AdaBoost's effectiveness in

classifying mental health conditions based on various features extracted from patient data. Key findings highlight AdaBoost's ability to improve classification accuracy through ensemble learning techniques, which combine multiple weak classifiers to produce a strong predictive model [2].

On the other hand, the paper **“Contextual emotion recognition Using Transformer-Based Models”** aims to propose an ensemble transformer model for analyse and detect emotions. This paper helps to aiming innovative approach to propose an ensemble model XML-R. The study demonstrates how these models outperform traditional methods in accurately recognizing emotions within varied contexts [3]. Transformer-based models, such as BERT and its successors, offer enhanced capabilities for emotion analysis due to their attention mechanisms and contextual embeddings. However, the paper also highlights challenges in adapting these models to diverse cultural contexts and dynamic emotional states. This paper emphasizes the benefits of combining textual information with audio and visual signals to achieve a more comprehensive understanding of emotional states.

The study demonstrates how additional context and cues that are not available in text alone are provided by multimodal approaches, which improve the accuracy of emotion detection. Nevertheless, there are still issues with ensuring that models can process and analyse various input types in an efficient manner as well as integrating multimodal data seamlessly.

Research Gap

Existing studies focused on only some mental health specific conditions. Many existing papers failed to capture different cultures express emotions differently and full complexity of emotions especially mixed or subtle emotions. Current models often overlook individual differences in emotional expression and mental health states. There is a need for models that can adapt to individual users over time, learning from their specific emotional and cultural contexts. Many models lack a deep understanding of context, which is crucial for sentiment analysis. This paper addresses this gap and achieving by incorporating ensemble model with Machine learning algorithm.

Proposed Method

The proposed method exhibits the comprehensive approach to developing an advanced, culturally adaptive, and multimodal mental health monitoring using XLM-R with Random Forest and Gradient boosting algorithm. Initially the textual data are collected from various sources such as social media, forums and clinical notes. Then the text data are pre-processed to remove noise and handle missing data. After pre-processing, the text data is prepared for model training by using tokenization, lemmatization. Then the model dataset is used to train the XLM-R model, the dataset is annotated with emotion labels, it ensuring a comprehensive range of emotions is represented (eg. happiness, sadness, anger, fear, surprise). To extract contextual embeddings from textual data the fine-tuned XLM-R model is used. Then Random Forest algorithm is applied for selecting more relevant features from extracted combined set, it helps in identifying key emotional features. After feature selection, the dataset is prepared for final training by combining selected features from Random Forest. To classify emotions accurately the Gradient Boosting Machine is trained (e.g., XGBoost) on the selected features, GBMs are powerful for capturing non-linear relationships and interactions between features, enhancing the model's performance. This detailed proposed method effectively combines the strengths of XLM-R, Random Forest, and Gradient Boosting Machine to create a robust, comprehensive, and privacy-preserving system for enhancing text-based mental health monitoring. By leveraging XLM-R for mental health monitoring, we aimed to improve more accuracy in detection.

Phases of Work

Phase 1: Data Collection and Pre-processing

Data Collection:

- Gather multilingual textual data from diverse sources (social media platforms, mental health forums, clinical notes)
- Ensure cultural and linguistic diversity in the dataset
- Collect data across multiple languages to support cross-lingual capabilities
- Implement ethical data collection protocols with proper consent mechanisms

Data Pre-processing:

- Remove noise, spam, and irrelevant content
- Handle missing data using appropriate imputation techniques
- Perform text normalization (lowercasing, removing special characters)
- Apply tokenization and lemmatization
- Create emotion annotation labels (happiness, sadness, anger, fear, surprise, etc.)
- Implement privacy-preserving techniques for sensitive mental health data

Phase 2: Model Development and Feature Engineering**XLM-R Fine-tuning:**

- Fine-tune pre-trained XLM-R model on the culturally diverse, annotated dataset
- Implement cross-lingual training to capture cultural nuances in emotional expression
- Extract contextual embeddings from processed textual data
- Validate model performance across different languages and cultural contexts

Feature Selection and Engineering:

- Apply Random Forest algorithm for feature selection from XLM-R embeddings
- Identify key emotional and contextual features that are most predictive
- Create combined feature sets that incorporate cultural and linguistic markers
- Optimize feature dimensionality for efficient processing

Phase 3: Classification and Evaluation**Gradient Boosting Implementation:**

- Train Gradient Boosting Machine (XGBoost) on selected features
- Optimize hyperparameters for maximum classification accuracy
- Implement ensemble methods combining XLM-R, Random Forest, and GBM outputs
- Develop real-time prediction capabilities

Model Validation and Testing:

- Conduct a comprehensive evaluation across multiple cultural and linguistic groups
- Perform cross-validation to ensure model generalizability
- Compare performance against baseline models and existing approaches
- Implement privacy and ethical compliance testing

Novelty of This Research Work**Hybrid Architecture Innovation**

The research presents a novel three-stage hybrid approach combining:

- XLM-R for cross-lingual contextual understanding - addresses cultural adaptability gaps in existing models
- Random Forest for intelligent feature selection - leverages ensemble learning for robust feature extraction
- Gradient Boosting for final classification - captures non-linear relationships and interactions

This amalgamation is distinctive as it integrates profound learning capabilities with the interpretability of traditional machine learning, an aspect that existing datasets and methodologies fail to comprehensively address.

Primary Dataset: GoEmotions

- Fine-tune XLM-R on GoEmotions' 27 emotion categories
- Establish baseline performance with Random Forest feature selection
- Train initial Gradient Boosting classifier

Go Emotions is a corpus of 58k carefully curated comments extracted from Reddit, with human annotations to 27 emotion categories or Neutral.

- Number of examples: 58,009.
- Number of labels: 27 + Neutral.
- Maximum sequence length in training and evaluation datasets: 30.

On top of the raw data, we also include a version filtered based on reter-agreement, which contains a train/test/validation split:

- Size of training dataset: 43,410.
- Size of test dataset: 5,427.
- Size of validation dataset: 5,426.

The emotion categories are: admiration, amusement, anger, annoyance, approval, caring, confusion, curiosity, desire, disappointment, disapproval, disgust, embarrassment, excitement, fear, gratitude, grief, joy, love, nervousness, optimism, pride, realization, relief, remorse, sadness, surprise.

Data Format

Our raw dataset, split into three csv files, includes all annotations as well as metadata on the comments. Each row represents a single rater's annotation for a single example. This file includes the following columns:

- text: The text of the comment (with masked tokens, as described in the paper).
- id: The unique id of the comment.
- author: The Reddit username of the comment's author.
- subreddit: The subreddit that the comment belongs to.
- link_id: The link id of the comment.
- parent_id: The parent id of the comment.
- created_utc: The timestamp of the comment.
- rater_id: The unique id of the annotator.
- example_very_unclear: Whether the annotator marked the example as being very unclear or difficult to label (in this case they did not choose any emotion labels).
- separate columns representing each of the emotion categories, with binary labels (0 or 1)

The data we used for training the models includes examples where there is agreement between at least 2 raters. Our data includes 43,410 training examples (train.tsv), 5426 dev examples (dev.tsv) and 5427 test examples (test.tsv). These files have *no header row* and have the following columns:

1. text
2. comma-separated list of emotion ids (the ids are indexed based on the order of emotions in emotions.txt)
3. id of the comment

Architecture

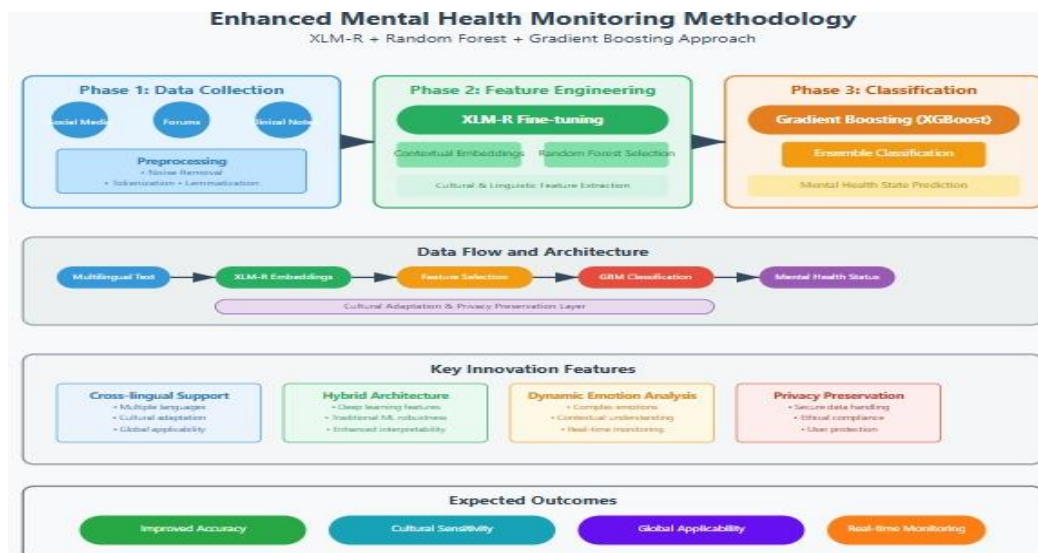


Figure 2: Architecture

III. Conclusions

69 papers that are pertinent to NLP applied to occupational exposure research have been manually examined for this work. Conclusions: Our findings indicate that

(i) more articles have been published that concentrate on using natural language processing (NLP) in exposure and epidemiological research, and

(ii) the majority of these articles make use of already-available NLP tools.

(i) The most widely used method is traditional machine learning.

It is anticipated that the accuracy of emotion identification across a variety of textual material will be greatly increased by combining XLM-R with machine learning methods. It is anticipated that this cultural sensitivity would improve the model's suitability and efficacy in a range of demographics, making it an invaluable instrument for monitoring mental health around the world. To enhance cultural adaptation in sentiment analysis, XLM-R (Cross-lingual Roberta) can be optimised on culturally diverse datasets and is built to handle multiple languages.

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