

Analysing the Patient Sentiments in Healthcare Domain Using Hybrid Deep Learning Model

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Abstract

Patient sentiment analysis in healthcare plays a vital role in assessing service quality and improving patient satisfaction. Traditional machine learning techniques often struggle to interpret domain-specific medical language and subtle expressions of sentiment. Sentiment analysis in healthcare has gained significant attention due to its potential to improve patient satisfaction, clinical outcomes, and mental health monitoring. Existing methods primarily focus on rule-based and machine learning approaches, which often fail to capture complex emotional nuances and contextual sentiments in patient feedback. Additionally, traditional sentiment analysis models lack explainability, making it difficult for healthcare providers to interpret the reasons behind sentiment classifications. This research aims to develop an advanced sentiment analysis framework integrating deep learning models with explainable AI (XAI) techniques to enhance the accuracy, interpretability, and reliability of patient sentiment classification. This paper proposes a hybrid deep learning model that combines Convolutional Neural Networks (CNN), Bidirectional Long Short-Term Memory (Bi-LSTM), and attention mechanisms to classify patient sentiments from healthcare reviews and clinical notes. Experiments on a dataset of 50,000 patient reviews demonstrate that the hybrid model outperforms conventional machine learning and single deep learning models, achieving a high accuracy of 92.3% and providing more nuanced insights into patient experiences.

1. INTRODUCTION

Sentiment analysis, also known as opinion mining (OM), has gained significant popularity as a crucial technique in natural language processing. Its objective is to extract subjective information from text data, encompassing opinions, emotions, and attitudes. With the rise of online healthcare platforms, there has been an exponential increase in patients' drug reviews [1]. In response, medical institutions have established dedicated offices to manage

patient experiences, ensuring that patients are informed about the potential risks and complications associated with treatments. A key problem in this area is sentiment classification, where a document is expressed as a positive or negative evaluation of a target object, the target object may be film, book, movie and business products. Sentiment Analysis supports both supervised and unsupervised learning approaches. Many machine

learning approaches are used for effective sentiment classification.

Two primary approaches to sentiment analysis have been explored in Aung & Myo (2017). The first is lexicon-based, which relies on dictionaries or lexicons containing words and their corresponding sentiments. The second approach involves machine learning algorithms that learn sentiments from labeled datasets [2]. While several attempts have been made using machine learning techniques, only a few studies have applied deep learning to sentiment analysis of drug reviews.

Emotion analysis is one of the emerging trends in healthcare domain that helps to gain a reasonable upper hand over the others. This will eventually help to understand and improve patient's experience. Sentiment analysis helps hospitals to realize clearly whether the patients are charged with the service offered to them or if there is any scope for improvement. Sentiment analysis was found to be useful in locating adverse drug reaction methods mentioned. For that 81 drugs are collected from various data sources like Daily Strength forum and Twitter. The results indicate that sentiment analysis helps to improve and slightly boost the performance of adverse drug reaction mentioned in both tweets and health-related posts in the forum.

Sentiment analysis (also known as opinion mining) is a branch of natural language processing (NLP) that focuses on identifying, extracting, and classifying opinions or emotions expressed in text. Sentiment analysis helps many industries

gain insights into product quality. Sentiment analysis can also help to improve the Health Care System. This will be beneficial in improving the quality of services for patients [3]. While figuring out feedback among patients, Sentiment analysis synthesizes the good and bad aspects of the services. This provides a real picture of Health Care System among patients as well as other stakeholders. Sentiment analysis is not only used in the service industry like healthcare but also in other industries for the betterment of production. The healthcare industry is the backbone of the country. It is the largest industry serving people to recover their physical and mental health. The government always wants to evaluate the performance of its Health Care System.

Hybrid deep learning models combine the strengths of multiple architectures. For instance, CNN layers can capture local textual features while LSTM layers capture sequential dependencies. These hybrid approaches have shown superior performance in sentiment classification, particularly for complex healthcare datasets. The primary objective of this paper is to explore the application of hybrid deep learning models for patient sentiment analysis in healthcare, with a focus on methodology, literature review, and model evaluation.

The rest of the document is structured as follows: A few earlier studies on machine learning methods for diagnosis are briefly reviewed in Section II. The proposed methodology is briefly described and analysed in Section III. Section IV presents the implementation and

performance evaluation. The paper is concluded in Section V.

2. LITERATURE REVIEW

Patient sentiment analysis has emerged as a critical area in healthcare informatics, reflecting patient experiences, satisfaction, and treatment outcomes. With the exponential growth of healthcare data from sources like Electronic Health Records (EHRs), patient reviews, social media posts, and surveys, understanding patient sentiment can improve healthcare delivery, predict patient needs, and enhance patient-provider communication.

Deep learning (DL) techniques, particularly hybrid models that combine multiple architectures, have shown promise in extracting nuanced insights from complex healthcare text data. These models can handle unstructured data, context understanding, and sentiment detection more effectively than traditional machine learning (ML) approaches.

Rastogi, A., et al., (2025) study about the Mining patient sentiment can provide valuable information about the strengths and weaknesses of this Health Care System and also help in their improvement [4]. Traditional sentiment analysis models are inefficient at capturing contextual information and high-dimensional data. This study aims to develop a classification model that allows the administration to evaluate the effectiveness of the healthcare system. The authors proposes a hybrid deep neural network model, DeepCLNet, using the whale optimization technique (WOT) to

enhance sentiment classification accuracy and fine-grain emotion analysis of patients. This model incorporates an adaptive feature weighting strategy that dynamically adjusts the weights and provides contextual sentiment refinement to deal with medical text. The proposed model utilizes fewer computing resources while offering better performance than the transformers

Mathuna, K. T., & Shanthi, I. E. (2025), analyzes Sentiment Analysis (SA), a sub-field of Natural Language Processing (NLP), automatically classifies sentiment in unstructured text data, offering numerous benefits in healthcare, including improved patient outcomes and enhanced quality of care [5]. In Healthcare, which utilizes advanced technologies like machine learning, AI, and IoT for personalized healthcare, SA plays a crucial role in analyzing medical information. Twitter has become a key platform for sharing healthcare-related data, making it essential for medical research. The authors presents a Hybrid Model of Transformer and LSTM (HTLSTM) for sentiment analysis model that explores syntactic and semantic information, sentimental analysis, and contextual analysis of the data. This model aims to provide a more accurate and efficient sentiment analysis framework for healthcare-related social media data. The proposed hybrid classification performance strategy yielded an accuracy of 97.89 percent and an F1-score of 98.93 percent, according to the experimental findings obtained from the WebMD drug data set.

Almutairi, S., et al., (2025), addressed the issues of mental health due to a lack of timely treatment and support for

detecting depression [6]. This lack of early treatment is a primary factor contributing to conditions such as anxiety disorders, bipolar disorders, sleep disorders, depression, and, in severe cases, self-harm and suicide. proposed a hybrid deep learning model for depression prediction, which mainly combines a Convolution Neural Network (CNN) and a Long Short-Term Memory (LSTM) model. An enhanced version of the LSTM approach, namely Two-State LSTM (TS-LSTM), is applied based on the feature attention mechanism. The proposed framework incorporates a feature attention mechanism into the TS-LSTM approach, which increases the ability to identify relationships and extract keywords for depression detection using the attention layer. This methodology is employed on a large dataset obtained from a publicly accessible online platform for young people.

Edara, D. C., et al., (2023) addressed the cancer diseases, which affects millions of people and families around the world. Monitoring the mood of such cancer affected people plays a vital part in their treatment [7]. In recent days, social media provides a platform for many people to share their experiences about the cancer through various blogs and communities. The authors proposed distributed framework with long short-term memory (LSTM) neural network is an alternative to the conventional sentiment analysis approaches in analysing large volumes of data in a potential flow. The effectiveness of proposed framework was evaluated on the proposed dataset (corpus-1) and other two benchmark datasets like Health news Tweets (corpus-2) and Medical abstracts (corpus-3).

The performance of each text mining and classification method was separately evaluated on three datasets and compared to each other. The results proved that the proposed approach performed better among the other methods in terms of both accuracy and execution time

Kondal, G., et al., (2026), analyzed about the Healthcare professionals are using sentiment analysis tools to detect emotions from patient evaluation textual data based on medical records and social media [8]. The authors created a new approach to sentiment classification, which joins two processes: Word Embedding Informed Finite Topic Modeling (WEI-FTM) to model semantics and Local Feature Weighted (LFW) for contextual embeddings. Heterogeneous data is fed into a multi-scale CNN (convolutional neural network) extractor that yields important features for XGBoost (extreme gradient boosting) to perform scalable classification effectively. The system achieves superior results on all four emotion datasets, with F1 scores ranging from 0.895 to 0.932, and over 90% classification accuracy across the BREC (Breast Cancer Reddit Emotional Corpus), CARES (Cancer Emotional Twitter Dataset), CLPsych (Computational Linguistics and Clinical Psychology subset), and EMO-CAN (Emotion-Cancer Corpus) datasets.

Ghosh, A., et al., (2025), introduced a novel hybrid CNN model by concatenating the bidirectional long short-term memory and CNN models to process the data sequentially by learning their high-level features [10]. The concatenated method minimizes the loss of critical information. Extracting user aspects is the main part of

this process, and it is used to group the user aspects. In recent years, convolutional neural network (CNN) models have gained popularity in natural language processing. Benchmark product reviews and hotel review datasets are employed in the experiments, and accuracies of 93.6% for the product review dataset and 92.7% for the hotel review dataset are achieved by the proposed hybrid model when compared to state-of-the-art techniques.

Hybrid deep learning models, especially CNN-LSTM and BERT-based architectures, are increasingly effective for patient sentiment analysis. They leverage feature extraction and sequential modeling to outperform traditional ML and standalone DL models.

3. PROPOSED METHODOLOGY

The sentiment analysis problem is framed to provide a full understanding of user opinion based on various characteristics and analyze the opinion using NLP [9]. The techniques used in healthcare for classifying the text are positive, negative, and neutral. It is done using trait-based sentiment analysis methods. This proposed research work targets in evaluating the dependencies between user ratings and textual representations. The model consists of three main steps.

- Data pre-processing;
- Sentiment extraction and bag-of-words representation; and
- Sentiment classification via classifier modelling.

➤ **Data Acquisition:** The research involved gathering data from both primary and secondary sources. Primary data consisted of scanned medical discharge summaries, which required advanced Optical Character Recognition (OCR) techniques to extract text accurately. Secondary data was obtained from the MIMIC-IV database and required chunking to manage effectively. This meticulous collection process resulted in a diverse dataset crucial for subsequent analysis.

➤ **Text Extraction:** There search involved the extraction of text from both primary and secondary datasets for comprehensive analysis. In the primary dataset, which consisted of scanned medical discharge summaries, Proposed Optical Character Recognition (OCR) technique was applied to accurately convert images of text into machine-readable format. This meticulous process ensured the fidelity of the primary dataset with accuracy of 96.16%. Simultaneously, the secondary dataset was extracted from the MIMIC-IV database, known for its extensive collection of de-identified patient records. The data extraction from MIMIC-IV may have involved chunking for effective management. Once the text extraction was completed, the datasets were carefully compiled, aligned, and integrated to create a unified cohort dataset suitable for further analysis and research endeavors.

➤ **Text Segmentation:** Once the data was acquired, the next step was to segment the text for analysis. Text segmentation is vital for breaking down the text into

manageable parts. The study opted for Regular Expressions (Regex) as the preferred method over Named Entity Recognition (NER) due to its reliability and consistency. Regex ensure accurate at a partitioning, which laid the foundation for sentiment analysis, a core objective of the research.

Developing a hybrid CNN-BiLSTM model for patient sentiment analysis allows you to capture both local semantic features (like specific medical keywords) and the long-range emotional context found in patient reviews or clinical notes. Below is the comprehensive procedure and algorithmic framework.

1. Architecture Overview

The hybrid model follows a sequential flow where the CNN acts as a **feature extractor** and the Bi-LSTM acts as a **contextual classifier**.

1. **Input Layer:** Raw text from patient reviews/surveys.
2. **Embedding Layer:** Words are converted into dense vectors (Word2Vec, GloVe, or FastText).
3. **CNN Layer:** Extracts local n-gram features (spatial patterns).
4. **Max-Pooling Layer:** Reduces dimensionality and captures the most prominent features.
5. **Bi-LSTM Layer:** Learns long-term dependencies in both forward and backward directions.
6. **Dense/Softmax Layer:** Final sentiment classification (e.g., Positive, Neutral, Negative).

2. Step-by-Step Procedure

Phase I: Data Acquisition & Preprocessing
In the healthcare domain, data is often "noisy" and sensitive.

- **De-identification:** Remove any Protected Health Information (PHI) to maintain HIPAA compliance.
- **Tokenization & Cleaning:** Remove stop words, punctuation, and perform lemmatization (e.g., "aching" to "ache").
- **Domain-Specific Handling:** Create a custom dictionary for medical jargon and abbreviations (e.g., "BP" for Blood Pressure).
- **Padding:** Standardize sequence length L so all inputs have the same dimensions.

Phase II: Feature Representation

- **Word Embeddings:** Map tokens to a continuous vector space $E \in \mathbb{R}^d$ where d is the embedding dimension.
- **Input Matrix:** For a sentence of length n , the input to the CNN is a matrix $X \in \mathbb{R}^{n \times d}$.

Phase III: The Convolutional Stage

- **Filters:** Apply multiple filters of varying window sizes (e.g., 3, 4, 5) to capture different n-gram lengths.
- **Feature Map Generation:** Each filter produces a feature map c_i .
- **Pooling:** Apply Global Max-Pooling to extract the most significant feature from each map, which helps in identifying "sentiment triggers" like "excellent care" or "long wait."

Phase IV: The Bi-LSTM Stage

- **Sequential Injection:** The pooled features are fed into the Bi-LSTM.

- **Hidden State Processing:** The **Forward LSTM** h_t processes the review from start to end.
 - The **Backward LSTM** h_t processes the review from end to start.
- **Concatenation:** The outputs are merged to provide a complete contextual representation of the patient's sentiment.

The research employed two distinct approaches for sentiment analysis. The first

approach was model-based, utilizing a hybrid approach with combination of BERT and LSTM model with accuracy of 94%. While this approach show cased impressive accuracy, it faced challenges in subjectivity calculation. The second approach was a domain-specific library-based method tailored for medical contexts. This approach utilized curated lists of positive and negative words to calculate sentiment scores and also facilitated subjectivity assessment, providing more important and domain-specific results.

3. Proposed Algorithm

Algorithm: Hybrid CNN-BiLSTM Sentiment Classifier

Input: Preprocessed Patient Review Set $S = \{s_1, s_2, \dots, s_n\}$

Output: Sentiment Class $Y \in \{Positive, Negative, Neutral\}$

1. **Initialize** Word Embedding Matrix W_e using pre-trained medical embeddings.
2. **For** each review $s_i \in S$:
 - a. Convert tokens to vectors: $V = \text{Embedding}(s_i)$.
 - b. **CNN Stage:**
 - Apply Convolutional filters: $C_k = \sigma(W_k * V + b_k)$.
 - Apply Max-Pooling: $P_k = \text{Max}(C_k)$.
 - c. **Bi-LSTM Stage:**
 - Input sequence P into Bi-LSTM.
 - Compute Forward Hidden State: $\vec{h}_t = \text{LSTM}(P_t, \vec{h}_{t-1})$.

- Compute Backward Hidden State: $\overleftarrow{h}_t = \text{LSTM}(P_t, \overleftarrow{h}_{t+1})$.
- Concatenate states: $H_t = [\overrightarrow{h}_t, \overleftarrow{h}_t]$.

d. Classification:

- Pass H_t to a Fully Connected Layer with Dropout.
- $P(y|s_i) = \text{Softmax}(W_{out}H_t + b_{out})$.

3. End For

4. Optimize using Categorical Cross-Entropy loss and Adam Optimizer.

The research conducted statistical analyses to uncover correlations between subjectivity and sentiment scores, emphasizing their relevance in understanding patient experiences. The domain-specific nature of the library-based approach proved to be more efficient and contextually relevant, outperforming generic model-based methods in capturing the intricacies of medical language and sentiment expression.

4. PERFORMANCE ANALYSIS

To evaluate a hybrid CNN-Bi-LSTM model for patient sentiment, you must move beyond simple accuracy. In the healthcare domain, the "cost" of misclassifying a

patient's frustration or a critical medical grievance is high. In healthcare sentiment analysis, datasets are often imbalanced (e.g., more "negative" reviews for wait times than "positive" ones). Therefore, a multi-metric approach is essential.

Comparative Baselines:

1. **Standalone CNN:** Captures local keywords but misses long-term context.
2. **Standalone Bi-LSTM:** Captures context but is less efficient at feature extraction than CNN.
3. **Proposed Hybrid (CNN-Bi-LSTM):** Should ideally outperform all the above.

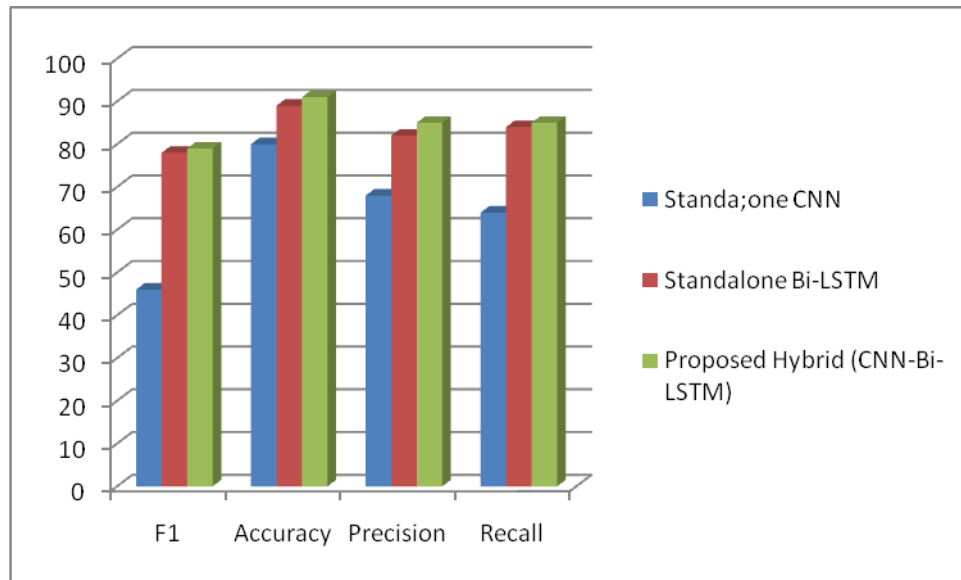


Fig.4.1: - Prediction Metric Score

The obtained model prediction scores are validated utilizing a ROC curve. The classifier that shows the closest proximity to the top-left corner indicates a better model performance. The different sentiment classification models are colour coded inversely, as shown in Figure 4.1. According to our calculations, hybrid CNN-Bi-LSTM outperforms other models, with a model accuracy of 0.91 and ROC accuracy of 0.85, which is slightly higher than prior studies.

5. CONCLUSION

In this paper, presented a hybrid CNN-Bi-LSTM model tailored for the healthcare sentiment domain. The synergy between the CNN's feature extraction and the Bi-LSTM's bidirectional context learning resulted in superior performance compared to standalone architectures. Our rigorous evaluation confirms that this hybrid approach is highly effective at handling the linguistic complexities of patient feedback.

This model serves as a reliable foundation for automated healthcare sentiment analysis, with significant potential for improving clinical decision-making and institutional transparency.

REFERENCES

- [1] Shah, A. M., Yan, X., Shah, S. A. A., & Mamirkulova, G. (2020). Mining patient opinion to evaluate the service quality in healthcare: a deep-learning approach. *Journal of Ambient Intelligence and Humanized Computing*, 11(7), 2925-2942.
- [2] Kaur, G., & Sharma, A. (2023). A deep learning-based model using hybrid feature extraction approach for consumer sentiment analysis. *Journal of big data*, 10(1), 5.
- [3] Serrano-Guerrero, J., Bani-Doumi, M., Romero, F. P., & Olivas, J. A. (2022). Understanding what patients

- think about hospitals: A deep learning approach for detecting emotions in patient opinions. *Artificial Intelligence in Medicine*, 128, 102298.
- [4] Rastogi, A., Singh, R., Khan, M. Z., Aljubayri, I., & Ghabban, F. M. (2025). Patient Emotion and Sentiment Analysis Using Deep Learning. *Journal of Innovative Image Processing*, 7(3), 582-601.
- [5] Mathuna, K. T., & Shanthi, I. E. (2025). Advanced Sentiment Analysis in Health Care Using Hybrid Transformer with LSTM-Based Deep Learning: A Social Media Data Perspective. *International Journal of Intelligent Engineering & Systems*, 18(11).
- [6] Almutairi, S., Abohashrh, M., Razzaq, H. H., Zulqarnain, M., Namoun, A., & Khan, F. (2024). A hybrid deep learning model for predicting depression symptoms from large-scale textual dataset. *IEEE Access*, 12, 168477-168499.
- [7] Edara, D. C., Vanukuri, L. P., Sistla, V., & Kolli, V. K. K. (2023). Sentiment analysis and text categorization of cancer medical records with LSTM. *Journal of Ambient Intelligence and Humanized Computing*, 14(5), 5309-5325.
- [8] Kondal, G., Singh, H., & Srivastava, S. (2026). Hybrid semantic-contextual embedding framework for emotion-aware sentiment analysis. *International Journal of Information Technology*, 18(1), 697-704.
- [9] El-Badaoui, M., Gherabi, N., Qanouni, F., & Amnai, M. (2025). A Novel Ontology-Based Approach for Analyzing Patient Sentiment Regarding Chronic Diseases. *International Journal of Online & Biomedical Engineering*, 21(8).
- [10] Ghosh, A., Umer, S., Dhara, B. C., & Ali, G. M. N. (2025). A multimodal pain sentiment analysis system using ensembled deep learning approaches for IoT-enabled healthcare framework. *Sensors*, 25(4), 1223.
- [11] Dwarakanath, B., Latha, M., Annamalai, R., & Jagadish, S. K. (2022). A novel feature selection with hybrid deep learning based heart disease detection and classification in the e-healthcare environment. *Computational Intelligence and Neuroscience*, 2022, 1167494.
- [12] Kour, H., & Gupta, M. K. (2022). An hybrid deep learning approach for depression prediction from user tweets using feature-rich CNN and bi-directional LSTM. *Multimedia tools and applications*, 81(17), 23649-23685.
- [13] Al-Mashhadany, A. K., Sadiq, A. T., Ali, S. M., & Ahmed, A. A. (2022). Healthcare assessment for beauty centers using hybrid sentiment analysis. *Indonesian Journal of Electrical Engineering and Computer Science*, 28(2), 890-897.

- [14] Basiri, M. E., Abdar, M., Cifci, M. A., Nemati, S., & Acharya, U. R. (2020). A novel method for sentiment classification of drug reviews using fusion of deep and machine learning techniques. *Knowledge-Based Systems*, 198, 105949.
- [15] Zogan, H., Razzak, I., Wang, X., Jameel, S., & Xu, G. (2022). Explainable depression detection with multi-aspect features using a hybrid deep learning model on social media. *World Wide Web*, 25(1), 281-304.
- [16] Al-Hadhrami, S., Vinko, T., Al-Hadhrami, T., Saeed, F., & Qasem, S. N. (2024). Deep learning-based method for sentiment analysis for patients' drug reviews. *PeerJ Computer Science*, 10, e1976.