Hospital Recommendation using Sentimental Analysis

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ABSTRACT

In the current digital era, most patients depend on online reviews to make well-informed choices when selecting a hospital for their treatment. These reviews frequently provide valuable insights regarding hospital services, patient care, and overall experiences. Nevertheless, the vast number of patient reviews complicates the manual analysis and extraction of meaningful conclusions. Sentiment analysis, a subset of Natural Language Processing (NLP), presents an effective solution to this challenge by automating the extraction of subjective information from text. This project, entitled "Hospital Recommendation using Sentimental Analysis", seeks to create an automated system capable of analyzing patient reviews for hospitals and offering recommendations based on the sentiments expressed in those reviews. The system utilizes machine learning algorithms to categorize reviews into positive, negative, or neutral sentiments, thereby delivering valuable insights into public perception. By employing text mining techniques and sophisticated NLP methods, the system will scrutinize unstructured data from hospital reviews, empowering patients to make more informed decisions based on the perspectives of others. The foundation of the system comprises two main components: Sentiment Analysis and Recommendation System. The Sentiment Analysis model categorizes the review text into sentiment classifications, while the Recommendation System proposes hospitals that have garnered the most favorable reviews. Furthermore, the system will integrate patient preferences such as treatment type and location to enhance the personalization of hospital recommendations.

keywords: Hospital recommendation, sentiment analysis, natural language processing (NLP), machine learning, patient reviews, text mining, Naive Bayes, Support Vector Machine (SVM), Logistic Regression, TF-IDF, Word2Vec, review classification, personalized suggestions, recommendation engine.

I. INTRODUCTION

In the healthcare sector, hospitals play a crucial role in delivering medical services, and selecting the appropriate hospital can frequently be a challenging endeavor for patients. Numerous individuals depend on evaluations and feedback from former patients to make well-informed choices regarding which hospital to select for their treatment. With the advent of digital platforms, patients now convey their experiences through online reviews. These reviews serve as a significant source of patient sentiment, which can greatly impact the decision-making process for others. Nevertheless, manually sorting through a vast number of reviews to extract valuable insights is a labor-intensive and time-consuming task. This is where Sentiment Analysis becomes relevant, enabling us to automate the extraction of sentiment from textual data. Sentiment analysis employs natural language processing (NLP) and machine learning techniques to identify and categorize opinions, emotions, or sentiments conveyed in a text. This project centers on Hospital Recommendation utilizing Sentiment Analysis, which aims to develop a system capable of analyzing patient reviews and offering hospital recommendations based on the sentiment reflected in these reviews. By utilizing machine learning models and text mining techniques, the system will automatically determine whether the reviews are positive, negative, or neutral, assisting prospective patients in making informed decisions based on the sentiments expressed by others.

II. RELATED WORK

A thorough overview of opinion mining and sentim ent analysis is given by Pang and Lee (2008), who concentrate on methods for detecting and extractin g subjective information from text. They highlight both lexicon,based and machine learning approach es (e.g., Naïve Bayes, SVM, and MaxEnt) and disc uss important tasks like document-level, sentence,level and aspect,based sentiment cl assification. They also address issues like sarcasm, domain dependency, and negation handling, and th ey highlight the usefulness of sentiment analysis in domains such as product reviews, movie ratings, an d political discourse.[1]

In their groundbreaking distant supervision method for Twitter sentiment classification, Go, Bhayani, and Huang (2009) automatically classified tweets a s either positive or negative depending on whether emoticons were present.They were able to create a sizable training dataset using this technique withou t the need for manual annotation. Using characteristics like unigrams, bigrams, and P OS tags, they experimented with machine learning classifiers including Naïve Bayes, Maximum Entro py, and SVM.
Their findings illustrated the possibility of remote s upervision for extensive sentiment analysis on soci al media sites by showing that even basic classifier s may get respectable accuracy.[2]

Kim (2014) showed that pretrained word vectors in conjunction with a single convolutional layer can a chieve competitive performance across many NLP benchmarks by proposing a straightforward yet effi cient Convolutional Neural Network (CNN) archite cture for sentence,level classification tasks.The mo del demonstrated CNNs' capacity to capture seman tic information in text categorization by outperform ing conventional techniques without the requireme nt for intricate feature engineering.[3]

In their comprehensive review of recommendation systems, Choi et al. (2016) divided them into three categories: hybrid, content-based, and collaborative filtering.
The study addressed common issues including scal ability, cold,start issues, and data sparsity while dis cussing a variety of algorithms and their uses in ind ustries like ecommerce, film, and healthcare.[4]

Zhang and Zhang (2017) provided a thorough exa mination of opinion mining and sentiment analysis methods, encompassing both lexicon,based and ma chine learning techniquesThey highlighted the incr easing importance of sentiment analysis in social m edia and business intelligence while talking about the various levels of sentiment analysis—document, sentence, and aspect—and assessing the advantages and disadvantages of each approach.[5]

Joulin et al. (2017) presented "fastText," a lightweight and effective method for classifying texts that combines hierarchical softmax, n-grams, and basic bag-of-words features.Their approach was appropriate for large,scale text categorization problems since it produced results that were on par with deep learning models but required substantially less training time.[6]

Raj (2018) investigated the prediction of hospital ratings by sentiment analysis of online reviews.The study sought to emphasize the function of sentiment mining in healthcare decision,making by bridging the gap between qualitative viewpoints and quantitative hospital performance through the analysis of patient feedback using natural language processing techniques.[7]

A survey of supervised, unsupervised, and mixed machine learning approaches for sentiment analysis was conducted by Bansal and Sharma (2018).The study examined algorithms such as SVM, Naïve Bayes, and neural networks and assessed how well they applied to the analysis of opinions in a variety of fields, including social media, politics, and products.[8]

Shah (2017) examined a number of data mining methods for sentiment analysis, with an emphasis on feature extraction, classification models, and preprocessing stages.

The study focused on how sentiment,related insights can be extracted from big datasets using methods including clustering, association rule mining, and classification algorithms.[9]

To improve accuracy and customisation, Kumar and Gupta (2020) developed a hybrid recommendation system that combines content,based and collaborative filtering.By utilizing the advantages of both approaches in applications like movie or product suggestions, their system sought to get around the drawbacks of individual approaches, such as cold-start and sparsity. [10]

III. METHODOLOGY

Fig 3.1. Proposed Methodology

3.1. Data Collection

- Sources of Data:

The primary data used in this project is collected from public hospital review platforms, social media (e.g., Twitter, Facebook), online hospital feedback portals, and review datasets available in open-source repositories like Kaggle or UCI.

- Nature of Data:

The data is mostly unstructured text, written in informal language, slang, mixed languages (e.g., Hinglish), emoticons, and contains spelling mistakes, which makes preprocessing necessary.

3.2. Data Preprocessing

- Text Cleaning:

This step includes removing special characters, punctuation marks, HTML tags, stop words

(like "is," "the," "a"), and converting all text to lowercase for uniformity.

- Tokenization:

The text is split into smaller units called tokens (usually words or phrases), which helps in analysis and model feeding.

- Stemming and Lemmatization:

Words are reduced to their root form (e.g., "treating", "treated", "treatment" → "treat") using stemming or lemmatization to reduce vocabulary size and improve accuracy.

- Noise Removal:

Eliminates irrelevant symbols, numeric values, emojis, URLs, and usernames from the input reviews.

- Vectorization (Text to Numeric):

After cleaning, the text is transformed into numerical format using techniques like TF-IDF (Term Frequency-Inverse Document Frequency) or Bag of Words (BoW) so it can be fed into ML algorithms.

3.3. Sentiment Analysis Model Building

- Model Selection:

Machine Learning classifiers such as Support Vector Machine (SVM), Logistic Regression, Naive Bayes, or Random Forest are tested and trained to classify sentiment.

- Labeling the Sentiment:

The reviews are labeled as Positive, Negative, or Neutral based on the emotional content present in the feedback.

- Training the Model:

A large dataset is divided into training and testing sets (e.g., 80% training and 20% testing).

The model learns the relationship between words and sentiment from the training data.

- Validation and Accuracy Testing:

The model is evaluated using performance metrics such as Precision, Recall, F1 Score, and Accuracy to ensure correctness and efficiency.

3.4. Recommendation System Integration

- Sentiment Aggregation per Hospital:

All sentiments related to a particular hospital are aggregated to find average polarity. For example, if 80% of the reviews are positive, the hospital is considered high-rated.

- Ranking Mechanism:

Hospitals are ranked based on their sentiment score, location, and specialty availability. Personalized Recommendation (Optional):

With user preferences such as proximity, required department (e.g., cardiology), or past experience, the recommendation is further customized.

3.5.Visualization and Frontend Display

- Graphs & Charts:

Sentiment data is visualized using bar graphs, pie charts, word clouds, and time-based trends using libraries like Chart.js, Matplotlib, or Plotly.

- User Interface Integration:

The ML backend is integrated with the web interface or application so users can interactively view recommendations and submit feedback.

3.6. Feedback Loop and Model Retraining

- Continuous Learning:

New user reviews are continuously collected and stored. These are periodically used to retrain the model to ensure the recommendation engine evolves and improves with time.

- Feedback Evaluation:

User behavior (clicks, time spent, review accuracy) is analyzed to improve system prediction confidence.

IV. TECHNOLOGIES USED

The Flask-based personality prediction web application utilizes a modern technology stack that integrates machine learning, web development, and database management to deliver accurate and interactive personality assessments:

Python: The core programming language for backend development, machine learning model implementation, and data preprocessing.

Flask: A lightweight Python web framework used to build the web application, handle HTTP requests, manage user sessions, and integrate machine learning models for real-time predictions.

LightGBM: An advanced gradient boosting framework employed for efficient and scalable multi-class personality classification using decision tree algorithms.

CatBoost: A gradient boosting library optimized for handling categorical data, used alongside LightGBM for robust personality trait prediction.

HTML/CSS/JavaScript: Standard web technologies for building responsive and user-friendly front-end interfaces, enabling users to input data and view results interactively.

Jinja2: Flask's templating engine, used to dynamically render HTML pages based on user data and model predictions.

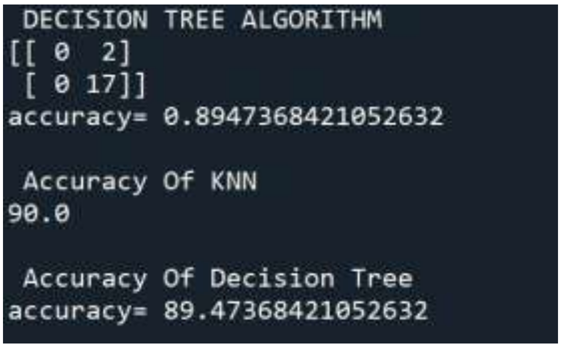
SQLite/MySQL: Relational databases used to securely store user information, prediction results, health tips, and queries for both users and administrators

Pandas/Numpy: Python libraries for data manipulation, analysis, and preprocessing before feeding data into machine learning models.

Scikit-learn: Used for additional data preprocessing, feature encoding, and evaluation metrics.Chart.js or Similar Visualization Libraries: For visualizing personality trait results and health tips within the web interface.

This combination of technologies ensures the application is scalable, secure, and user-friendly, providing both advanced machine learning capabilities and a seamless web experience.

V. RESULT



```
 DECISION TREE ALGORITHM
[[ 0  2]
 [ 0 17]]
accuracy= 0.8947368421052632

 Accuracy Of KNN
90.0

 Accuracy Of Decision Tree
accuracy= 89.47368421052632
```

Fig 5.1. Decision Algorithm

True Negatives (TN): 0 → The model predicted no correct negatives.

False Positives (FP): 2 → 2 instances were incorrectly classified as positive.

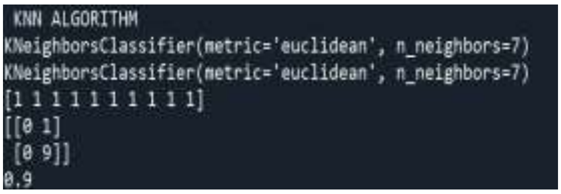
False Negatives (FN): 0 → No positive cases were missed.

True Positives (TP): 17 → 17 positive instances were correctly identified.

📌 Interpretation:

The model correctly identified all the actual positives.

It failed to correctly identify any actual negatives (possibly due to imbalance in the dataset).



```
KNN ALGORITHM
KNeighborsClassifier(metric='euclidean', n_neighbors=7)
KNeighborsClassifier(metric='euclidean', n_neighbors=7)
[1 1 1 1 1 1 1 1 1 1]
[[0 1]
 [0 9]]
0.9
```

Fig 5.2. KNN Algorithm

True Negatives (TN): 0 — No class 0 samples were correctly predicted.

False Positives (FP): 1 — One class 0 sample was incorrectly predicted as class 1.

False Negatives (FN): 0 — No class 1 samples were missed.

True Positives (TP): 9 — All 9 class 1 samples were correctly predicted.

📌 Interpretation:

The model performs perfectly on class 1 but fails to classify class 0 correctly.

This suggests the model is overfitting or biased toward class 1 (again, class imbalance may be an issue).

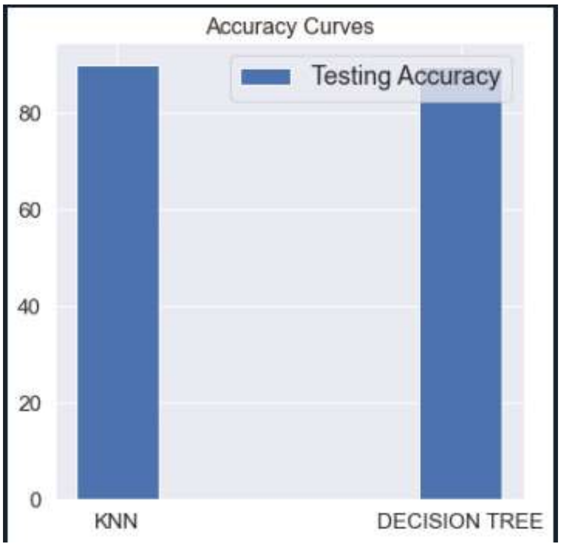


Fig 5.3. Accuracy Curves

Graph Components:

Title: Accuracy Curves

X-axis: Algorithm Names (KNN and DECISION TREE)

Y-axis: Accuracy Percentage (ranging from 0 to 100)

Bars: Represent the testing accuracy of each model

Legend: "Testing Accuracy" — indicates the metric being visualized.

📈 Interpretation:

KNN Accuracy: Slightly above 90%

Decision Tree Accuracy: Slightly below 90% (around 89.5%)

This matches the raw outputs seen in your earlier screenshots:

KNN Accuracy = 90.0%

Decision Tree Accuracy = 89.47%

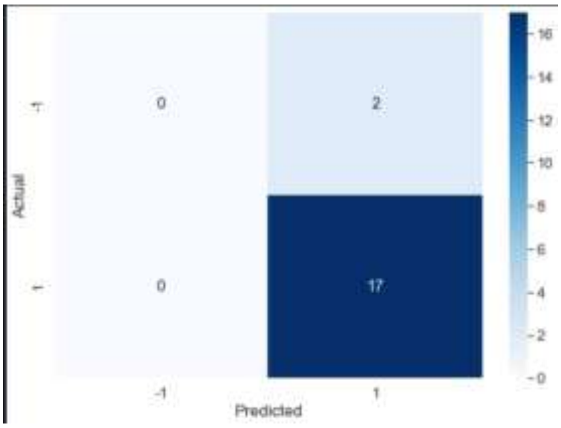


Fig 5.4. Conclusion Matrix

- The classifier **is very good at predicting class 1**, with a **true positive rate of 100%**.
- However, it **completely fails at identifying class -1**, with **false positive rate = 100%** for that class.
- This indicates **bias towards class 1**, which is likely due to:
  - **Class imbalance**
  - **Overfitting** to class 1 during training

VI. CONCLUSION

In this project, *Hospital Recommendation using Sentiment Analysis*, we have successfully demonstrated how Natural Language Processing (NLP) and machine learning techniques can be effectively utilized to simplify and enhance the hospital selection process for patients. By automating the analysis of patient reviews, the system provides meaningful sentiment-based insights, classifying reviews into positive, negative, or neutral categories. This not only reduces the manual effort required to interpret extensive reviews but also empowers patients to make informed decisions based on aggregated public opinion.

The integration of sentiment analysis with personalized recommendation algorithms allows the system to offer more accurate and user-centric hospital suggestions, considering factors like location, treatment type, and patient preferences. The combination of a user-friendly frontend, efficient backend API processing, and a robust machine learning model ensures the system's scalability and reliability in handling large volumes of data from various sources.

Furthermore, the system's continuous learning ability enables it to adapt and improve its performance over time as new data becomes available. This project not only addresses the limitations of existing systems that rely solely on ratings or raw text but also presents a scalable solution capable of evolving with the growing need for intelligent healthcare decision-support tools.

The developed model serves as a promising step towards enhancing healthcare accessibility and transparency, ultimately contributing to better patient satisfaction and trust in healthcare services.

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