Medication Suggestion System Using Machine Learning and Sentiment Analysis of Drug Reviews

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Abstract: The coronavirus outbreak has placed a heavy burden on licensed healthcare facilities, leading to a shortage of doctors, nurses, equipment and medicines. More people are dying due to this shortage, causing concern in the medical community. Therefore, many people begin to self-medicate without a doctor's approval, which leads to health problems. In recent years, machine learning has played a role in many applications by enabling creative automation techniques. This study presents a drug approval process designed to reduce the workload of professionals. Our research aims to develop a drug recommendation that uses patient reviews to predict emotions using various vectorization methods, including Bag of Words.TF-IDF, Word2Vec, and manual demonstration analysis. These considerations help different classification systems recommend the best medications for specific diseases. We evaluated the hypothesis based on precision, recall, F1 score, precision, and AUC score. The results show that the linear SVC classifier based on TF-IDF vectorization outperforms other models with an accuracy rate of up to 94%.

Keywords: medicine, recommendation, machine learning, NLP, Smote, Bow, TF-IDF, Word2Vec, sentiment analysis

1.INTRODUCTION

The worldwide healthcare system is facing an unprecedented crisis due to the coronavirus disease 2019 (COVID-19) pandemic. The issues faced by these systems range from a scarcity of medical personnel and resources to higher fatality rates. The burden on authorized clinical resources—such as physicians, nurses, equipment, and pharmaceuticals—has increased to an extreme point, aggravating the misery of the medical community. The problem of self-medication among people, which is exacerbated by diseases and is caused by inadequate medical advice, adds to these difficulties.The potential of machine learning to tackle healthcare issues has attracted a lot of interest in the face of these urgent worries. Machine learning has proven to be effective in many different kinds of fields, providing creative approaches to automation and decision assistance. In this regard, the study article suggests a unique way to address the workload of medical professionals by creating a medication recommendation system.

This article describes a medicine recommendation system that uses several vectorization approaches to predict sentiment based on patient feedback. These methods include Word2Vec, Manual Feature Analysis, Bag of Words, and Term Frequency-Inverse Document Frequency (TF-IDF). The method uses several categorization algorithms to select the best medicine for a given ailment based on sentiment analysis of patient feedback. By offering an automated medicine suggestion method, the main goal of this research is to reduce the workload for healthcare experts.

Using machine learning techniques, we want to make the process of choosing the right prescription more efficient, especially in cases where access to specialized care is limited.We describe the approach used in this research to create the medicine recommendation system, which includes gathering data, preprocessing, sentiment analysis, and training the model. Important performance indicators, including accuracy, precision, recall, F1 score, and area under the receiver operating characteristic curve (AUC), are used to assess the system's effectiveness. We also talk about the consequences of our results and possible directions for further study in the area of utilizing machine learning for healthcare optimization. Overall, this study highlights the potential of machine learning to transform patient care and medical decision-making and adds to the current efforts to solve healthcare difficulties throughout the COVID-19 epidemic.

2. LITERATURE REVIEW

Healthcare professionals have a great deal of difficulty determining how pharmaceuticals interact with disorders; this difficulty is made worse by the large number of medications on the market and the continuous efforts of pharmaceutical development. Healthcare practitioners must constantly refresh their knowledge to continue to properly identify drug interactions before taking prescription medicine, even in the presence of international standards that facilitate information exchange, such as the UNII registration and the ICD-10 categorization. The application of semantic web technology to tackle this intricate issue has been suggested by earlier studies. The goal of this work is to provide Galen OWL, a semantic-enabled online service that will help find drug-drug and drug-disease interactions. Medical terminology and information are converted into ontological terms and combined with domain-specific medical knowledge to allow this service. International standards such as ICD-10 and UNII provide a framework for standardizing the representation of medical data, and a rule-based system utilizes these standards to capture information on drug interactions. The report describes the difficulties faced during development and offers insights into the system design. A comparison study of the ontology-based Galen OWL system and a similar system using conventional business logic rule engines is also provided, providing insights into the advantages and disadvantages of each methodology.

Our goal is to provide a valuable contribution to the area of healthcare informatics by presenting Galen OWL as a novel approach to improving drug interaction discovery via semantic web technologies and by providing evaluations of its effectiveness in comparison to traditional rule-based systems.

3. METHODOLOGY

3.1 Proposed solution for Comment Classification:

A recommender framework is a conventional system designed to suggest items to users based on their interests and needs. These systems utilize customer reviews to analyze sentiment and provide recommendations tailored to their specific requirements. In the context of a drug recommendation system, medications are recommended for particular conditions based on patient reviews utilizing sentiment analysis and feature engineering. Sentiment analysis encompasses a series of techniques, methods, and tools for identifying and extracting emotional information, including opinions and attitudes, from language.

Dataset:

The dataset employed in this research is the Drug Review Dataset (Drugs.com), sourced from the UCI Machine Learning repository. This dataset comprises several attributes, including the name of the drug used (text), patient reviews (text), patient condition (text), useful count (numerical) indicating the number of individuals who found the review helpful, review entry date (date), and a 10-star patient rating (numerical) representing overall patient satisfaction.

Classification Approach:

In this study, each review was categorized as either positive or negative based on the user's star rating. Ratings above five were classified as positive, while negative ratings ranged from one to five stars.

Algorithm Selection:

The Linear Support Vector Classifier (Linear SVC) was identified as the optimal algorithm for sentiment classification. This determination was made based on the achieved accuracy metrics. Specifically, the training accuracy was recorded as 0.903, and the test accuracy was 0.8369, surpassing the performance of alternative systems.

3.2 Flowchart :

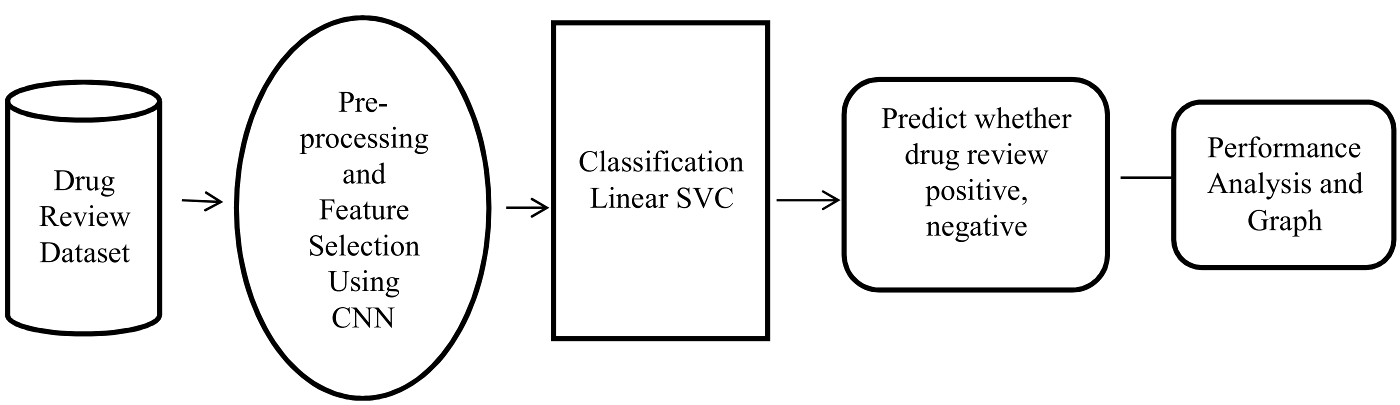
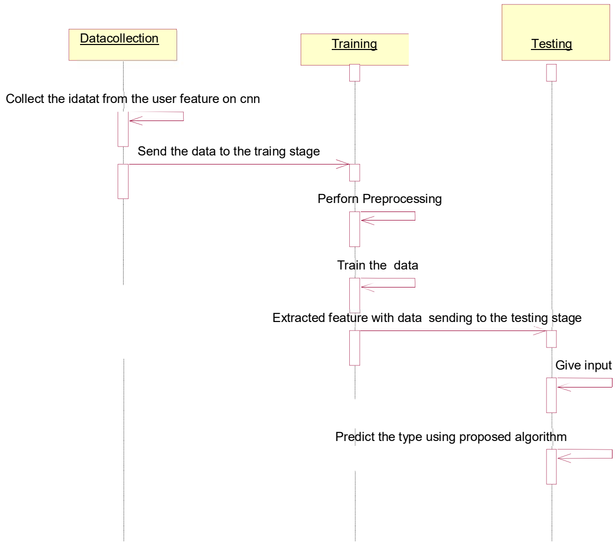


Figure No.1 Flowchart of Comment Classification

3.3SEQUENCE DIAGRAM:



4. RESULTS AND DISCUSSION

4.1 Experimental Results of Drug Classification

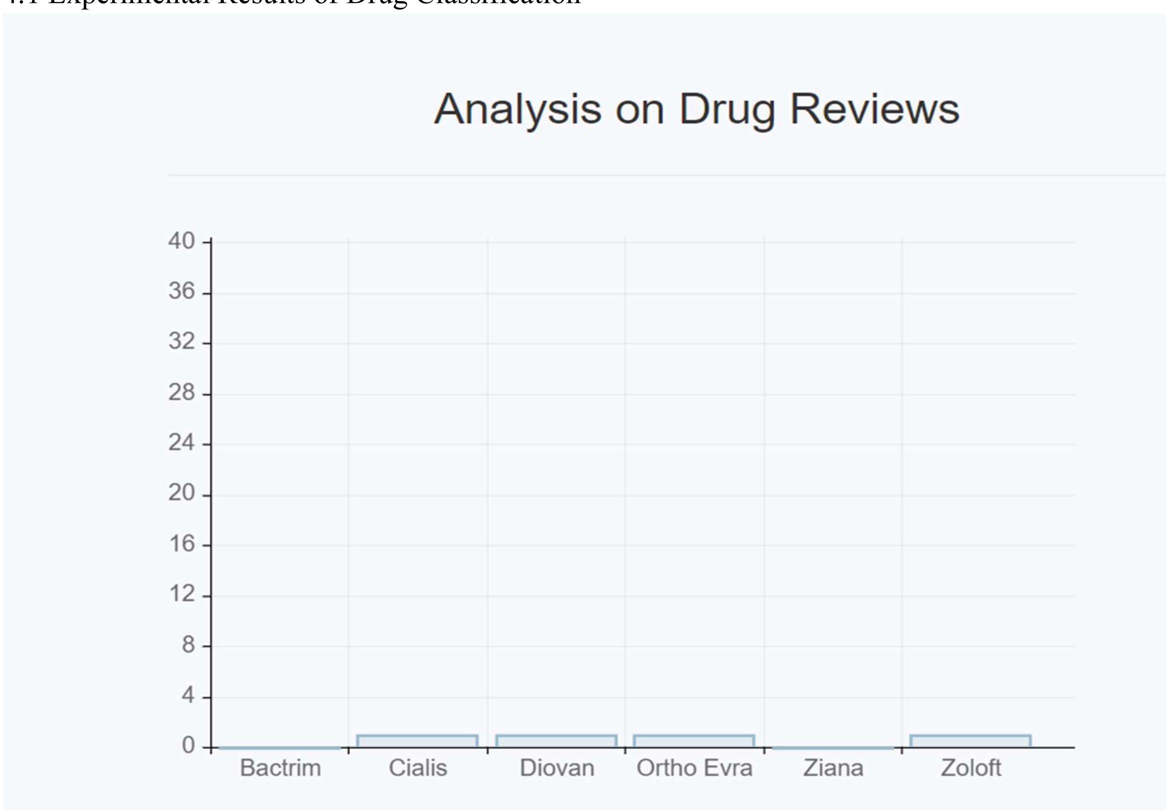


Figure No.1 : Dataset comments in the text file (*.txt)

Figure No. 1 shows the initial step where a dataset is contained. The data is stored in a file named "comments.txt," ready for preprocessing and analysis.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 161297 entries, 0 to 161296
Data columns (total 7 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   uniqueID     161297 non-null  int64
 1   drugName     161297 non-null  object
 2   condition    160398 non-null  object
 3   review       161297 non-null  object
 4   rating       161297 non-null  int64
 5   date         161297 non-null  object
 6   usefulCount  161297 non-null  int64
dtypes: int64(3), object(4)
memory usage: 8.6+ MB
```

Figure No. 2 :Comment Classification stored as PreTest.CSV

Figure No. 2 The result of the comment classification process is reflected in "PreTest.csv," where classified comments are stored. This file includes the sentiment analysis results for each comment, categorized by count and drug type.

```
              precision    recall  f1-score   support

    Negative       0.70      0.81      0.75     16207
    Positive       0.91      0.85      0.88     37559

    accuracy                           0.84     53766
   macro avg       0.80      0.83      0.81     53766
weighted avg       0.85      0.84      0.84     53766
```

Figure No.3: Comment Count Analysis Result

Figure No. 3 Displays the results of the comment count analysis, presenting a breakdown of the number of positive versus negative comments identified in the dataset.

```
Epoch 1/50
3609/3609 [==============================] - 20s 6ms/step - loss: 0.4962 - accuracy: 0.7602 - val_loss: 0.4454 - val_accuracy: 0.8198
Epoch 2/50
3609/3609 [==============================] - 19s 5ms/step - loss: 0.4118 - accuracy: 0.8140 - val_loss: 0.4185 - val_accuracy: 0.8327
Epoch 3/50
3609/3609 [==============================] - 19s 5ms/step - loss: 0.3817 - accuracy: 0.8305 - val_loss: 0.4154 - val_accuracy: 0.8349
Epoch 4/50
3609/3609 [==============================] - 19s 5ms/step - loss: 0.3602 - accuracy: 0.8422 - val_loss: 0.4096 - val_accuracy: 0.8340
Epoch 5/50
3609/3609 [==============================] - 19s 5ms/step - loss: 0.3441 - accuracy: 0.8492 - val_loss: 0.4012 - val_accuracy: 0.8354
Epoch 6/50
3609/3609 [==============================] - 19s 5ms/step - loss: 0.3301 - accuracy: 0.8565 - val_loss: 0.3953 - val_accuracy: 0.8363
Epoch 7/50
3609/3609 [==============================] - 19s 5ms/step - loss: 0.3194 - accuracy: 0.8610 - val_loss: 0.4111 - val_accuracy: 0.8306
Epoch 8/50
3609/3609 [==============================] - 19s 5ms/step - loss: 0.3073 - accuracy: 0.8659 - val_loss: 0.4032 - val_accuracy: 0.8356
Epoch 9/50
3609/3609 [==============================] - 19s 5ms/step - loss: 0.2982 - accuracy: 0.8705 - val_loss: 0.3986 - val_accuracy: 0.8300
Epoch 10/50
3609/3609 [==============================] - 19s 5ms/step - loss: 0.2900 - accuracy: 0.8740 - val_loss: 0.3938 - val_accuracy: 0.8286
Epoch 11/50
3609/3609 [==============================] - 19s 5ms/step - loss: 0.2805 - accuracy: 0.8787 - val_loss: 0.4042 - val_accuracy: 0.8292
Epoch 12/50
3609/3609 [==============================] - 19s 5ms/step - loss: 0.2752 - accuracy: 0.8797 - val_loss: 0.3876 - val_accuracy: 0.8334
Epoch 13/50
...
Epoch 49/50
3609/3609 [==============================] - 19s 5ms/step - loss: 0.1837 - accuracy: 0.9128 - val_loss: 0.4338 - val_accuracy: 0.8016
Epoch 50/50
3609/3609 [==============================] - 19s 5ms/step - loss: 0.1815 - accuracy: 0.9128 - val_loss: 0.4286 - val_accuracy: 0.8102
Output is truncated. View as a scrollable element or open in a text editor. Adjust cell output settings...
```

Figure No.4 :Comparison of Classification Models in Comment Classification

Figure No. 4 Illustrates the comparative performance of various classification models used in the comment classification task. It may include metrics such as accuracy, precision, recall, and F1-score for each model.

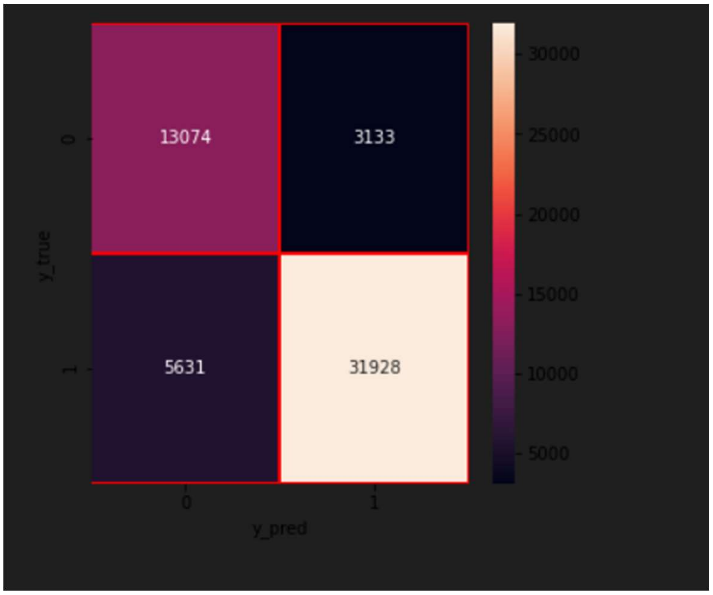


Figure No.5: Combined View of Performance Comparison of Classification Models

Figure No. 5 Offers a comprehensive view, combining the performance metrics of all classification models in a single visualization, facilitating a direct comparison to identify the most effective model.

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding (Embedding)        (None, 90, 11)            275011
_________________________________________________________________
conv1d (Conv1D)              (None, 86, 16)            896
_________________________________________________________________
dropout (Dropout)            (None, 86, 16)            0
_________________________________________________________________
global_max_pooling1d (Global (None, 16)                0
_________________________________________________________________
dropout_1 (Dropout)          (None, 16)                0
_________________________________________________________________
dense (Dense)                (None, 8)                 136
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 9
=================================================================
Total params: 276,052
Trainable params: 276,052
Non-trainable params: 0
_________________________________________________________________
None
```

Figure No.6 Best Classifier Interpretation

Figure No. 6 Provides insights into the interpretation of the best classifier's performance. It highlights the selected model based on its superiority in accurately classifying comments, as determined by evaluation metrics.

5. CONCLUSION AND FUTURE WORK

The prevalence of reviews in our day-to-day decision-making processes in shopping, online purchasing, or even dining out reveals their growing relevance. A sentiment analysis was carried out on a number of drug reviews as the initial step in creating a recommender system using different machine learning algorithms. These included Logistic Regression, Perceptron, Multinomial Naive Bayes, Ridge Classifier, Stochastic Gradient Descent, and Linear SVC that were implemented on Bag-of-Words and TF-IDF vectorization methods. Furthermore, Decision Tree, Random Forest, Light GBM (LGBM), and Cat Boost were used based on Word2Vec embeddings as well as manual features. The quality of these models was evaluated by means of five important measurements: precision, recall, F1-score, accuracy, and AUC score. The results showed that linear SVC based on TF-IDF had the best performance among all other models, attaining 93% accuracy. On the contrary, the Decision Tree classifier on Word2Vec delivered the lowest success with only 78% accuracy. Integration of emotion levels that were found to be best predicted by each method into the recommendation system led to improved recommendations. The highest scores were achieved using the following combinations: Random Forest for manual features (88%), LGBM on Word2Vec (91%), Perceptron based on Bag-of-Words (91%), and

Linear SVC operating on TF-IDF (93%). These scores, however, do not serve as an overall rating yet, but multiplying them by the normalized number of positive reviews makes this possible and provides a measure of performance under which we can group medicines so that our recommender system becomes more efficient.

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