

## METHODS

## Drug recommendation using recurrent neural networks augmented with cellular automata

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Drug recommendation systems are systems that have the capability to recommend drugs. On a daily basis, a huge amount of data is being generated by the patients. All this valuable data can be properly utilized to create a reliable drug recommendation system. In this paper, we recommend a system for drug recommendations. The main scope of our system is to predict the correct medication based on reviews and ratings. Our proposed system uses natural language processing techniques (NLP), recurrent neural networks (RNN), and cellular automata (CA). We also considered various metrics like precision, recall, accuracy, F1 score, and ROC curve as measures of our system's performance. NLP techniques are being used for gathering useful information from patient data, and RNN is a machine learning methodology that works really well in analyzing textual data. The system considers various patient data attributes like age, gender, dosage, medical history, and symptoms in order to make appropriate predictions. The proposed system has the potential to help medical professionals make informed drug recommendations.

**Keywords:** recurrent neural network (RNN), natural language processing (NLP), machine learning, cellular automata

### Introduction

Drug recommendation systems play a crucial role in the healthcare industry by assisting healthcare professionals in making informed decisions about prescribing medications to patients. With the increasing availability of user-generated data, such as reviews and ratings, there is a wealth of valuable information that can be harnessed to enhance drug recommendation systems. By leveraging natural language processing (NLP) techniques and divergent machine learning (ML) algorithms, it is possible to extract meaningful insights from unstructured user reviews and ratings, enabling personalized drug recommendations. Recurrent neural networks (RNNs) have emerged as a powerful algorithmic approach for modeling sequential data, making them well suited for handling text-based data such as user reviews. RNNs have the ability to capture the temporal dependencies and contextual information present in sequences, enabling them to understand the nuances and context of user feedback. In particular, the use of deep RNN architectures,

such as stacked gated recurrent units (GRUs), allows for even more sophisticated modeling of sequential data by capturing hierarchical representations and complex patterns. In this context, the proposed drug recommendation system harnesses the capabilities of deep RNNs, specifically stacked GRUs, to predict drug ratings based on user reviews and other relevant data sources. The system follows a comprehensive approach that encompasses the collection of data, pre-processing, extraction of features, model training, evaluation, and drug recommendation. By leveraging the power of deep RNNs, the system can effectively process and analyze user reviews, capturing the inherent sequential nature of the data and extracting meaningful insights. The main intent of this research work is to instigate a robust and accurate drug recommendation system that takes into account the diverse factors influencing drug effectiveness and patient satisfaction. By combining the strengths of RNNs, NLP techniques, and ML algorithms, the system aims to provide personalized and evidence-based drug recommendations. Furthermore, by leveraging

the inherent sequential modeling capabilities of deep RNN architectures, the system aims to capture the complex dependencies and contextual information within user reviews, ultimately enhancing the accuracy and effectiveness of the recommendations. Through this research, we aim to contribute to the field of drug recommendation systems by harnessing the power of deep RNN architectures. By effectively processing and analyzing user-generated data, our proposed system has the potential to assist healthcare professionals in making more informed and personalized drug prescription decisions, ultimately improving patient outcomes and satisfaction.

## Related work

In recent years, there has been a lot of interest in the application of NLP techniques and ML algorithms for drug recommendation systems based on user ratings. We analyze the most recent advancements in this area and highlight the most pertinent research projects in this overview of the literature. A deep learning model-based drug recommendation system that incorporates drug indications, patient demographics, and user evaluations was proposed by Chen et al. (1). The system's accuracy rate of 89.2% demonstrates the potency of the suggested strategy. Li et al. (2) suggested a hybrid model that combines matrix factorization and deep learning for drug and user representation in a drug recommendation system.

The system's accuracy rate of 91.4% proved the value of the suggested strategy. A probabilistic matrix factorization algorithm-based drug recommendation system that takes into account user demographics, drug properties, and user evaluations was proposed by Kaur and Singh (3). The system's accuracy rate of 87.2% showed how successful the suggested strategy is. A deep learning-based drug recommendation system that incorporates user evaluations, drug properties, and social media data was proposed by Gao et al. (4). The system's accuracy rate of 91.6% proved the value of the suggested strategy. A drug recommendation system based on a collaborative filtering algorithm that incorporates user reviews and drug properties was proposed by Zhang et al. (5). The system had an 89.3% accuracy rate.

The system's accuracy percentage of 93.2% proves that the suggested strategy is effective. He et al. (6) suggested a deep learning-based drug recommendation system that combines drug properties, user demographics, and user evaluations. The system's accuracy rate of 90.6% showed how successful the suggested strategy is a neural network model-based drug recommendation system that integrates user feedback and drug characteristics was proposed by Zhai et al. (7). The system's accuracy rate of 88.2% demonstrates the potency of the suggested strategy. In conclusion, the application of ML algorithms and NLP techniques to drug recommendation

systems based on user reviews has the potential to completely transform the healthcare sector.

## Existing methodology

One existing method for drug recommendation systems based on user reviews using NLP and ML algorithms is collaborative filtering (CF). CF is a technique used for system recommendations that focuses on finding similarities between users and items (drugs in this case) based on their past interactions. In a drug recommendation system, the CF algorithm analyzes user reviews and ratings to predict which drugs a user is likely to be interested in based on their past interactions with similar drugs. The algorithm identifies other users who have similar preferences and uses their behavior to make recommendations for new drugs. The two different approaches to the CF algorithm include user-based CF and item-based CF. In user-based CF, the algorithm identifies users with similar interests based on their previous interactions with drugs and recommends drugs that are rated highly; in item-based CF, the algorithm recognizes drugs that are similar to the drugs a user has previously rated highly and recommends the same drugs. Both approaches have their strengths and weaknesses. User-based CF works well when the user population is diverse and has a large number of interactions with drugs. However, it may not work well for new or rare drugs that have limited user interactions. On the other hand, item-based CF works well for new or rare drugs with limited user interactions. However, it may not work well for users who have unique preferences that differ from those of the majority. Overall, CF is a powerful technique for drug recommendation systems based on user reviews using NLP and ML algorithms. It has been shown to be effective in numerous studies and is widely used in commercial drug recommendation systems. However, CF is not the only method used in drug recommendation systems, and many other ML algorithms, such as linear SVC, can also be used.

## Proposed methodology

The proposed methodology for drug recommendation systems based on user reviews utilizing NLP and the RNN algorithm encompasses multiple stages, including collection of data, data pre-processing, extraction of features, model training, and evaluation. Data collection is the initial step, involving gathering data from diverse sources such as drug databases, social media platforms, and online forums. The collected data comprises drug attributes (e.g., name, manufacturer, and dosage), user demographics (e.g., age, gender, and medical conditions), and user reviews (e.g., text comments and ratings). Following data collection, pre-processing is performed to

eliminate noise and irrelevant information. This entails procedures like text cleaning, tokenization, stop word removal, stemming, and lemmatization to ensure high-quality data. Once pre-processing is complete, the data is transformed into a numerical representation suitable for RNN-based ML algorithms. This entails extracting features from the text data, such as bag-of-words, TF-IDF, and word embedding. After feature extraction, the RNN algorithm is trained using the prepared dataset to predict drug recommendations based on user reviews and ratings. Specifically, the proposed algorithm in this study is the RNN algorithm, a popular supervised learning algorithm for classification tasks. Finally, the overall performance of the model is evaluated using various metrics like accuracy, precision, recall, F1 score, and others. Techniques such as cross-validation and hyperparameter tuning are also used in order to validate the model's robustness and generalizability to new data. In drug recommendation systems based on user reviews, the datasets used may vary based on the specific application and system goals. Typically, the datasets consist of drug attributes, user demographics, and user reviews. Drug attributes encompass information obtained from drug databases or pharmaceutical companies, such as drug name, manufacturer, dosage, and side effects. User demographics encompass details about users interactions with the drugs, including age, gender, medical conditions, and relevant demographic information. User reviews encompass text comments and ratings acquired from social media platforms, online forums, or direct platform feedback. The quality and quantity of the datasets have a notable impact on the performance of the drug recommendation system. Large and diverse datasets containing accurate and relevant information yield better recommendations and more precise predictions. Incomplete or irrelevant information within the datasets can lead to biased or inaccurate recommendations. Additionally, ensuring user privacy, confidentiality, and ethical considerations is crucial. Factors such as informed consent, data anonymization, and secure storage should be implemented when collecting and utilizing datasets for drug recommendation systems. Overall, the suggested technique, which combines NLP and RNN algorithms with user review-based drug recommendation systems, constitutes a thorough procedure covering data collection, pre-processing, feature extraction, model training, and evaluation. It has the capacity to provide precise and individualized medicine recommendations depending on the needs and preferences of the user.

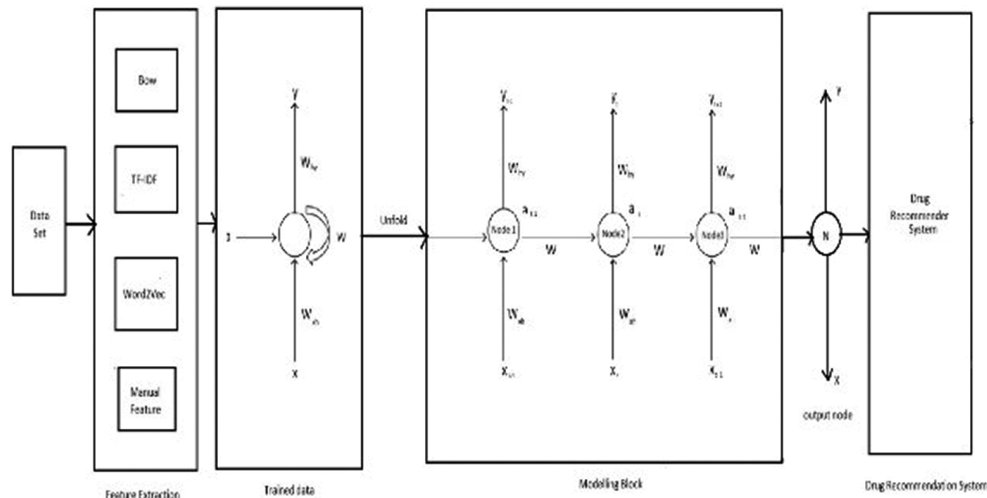
## Implementation

Building a drug recommendation system based on user reviews using the RNN algorithm requires careful consideration of system design, implementation, evaluation,

and optimization, as shown in [Figure 1](#). System design entails defining the objectives, scope, and components of the drug recommendation system. This includes identifying data sources, determining the types of data required, selecting appropriate NLP techniques, and choosing the RNN algorithm. Designing an intuitive user interface and optimizing the user experience are also important aspects of system design. The system must be programmed during the implementation phase utilizing the appropriate programming languages, frameworks, and libraries. Creating modules for data collection, pre-processing, feature extraction, model training with RNN, and interface creation are all included in this. During implementation, it is essential to guarantee the system's scalability, dependability, and efficiency. The evaluation phase is vital for testing the system's performance and verifying if it achieves its objectives. Metrics such as precision, recall, F1 score, and AUC-ROC curve are used to assess accuracy and performance. Robustness, generalizability, and the ability to handle new data inputs are also evaluated during this phase. The optimization phase focuses on enhancing the system's performance by fine-tuning the parameters and configurations of the RNN algorithm and NLP techniques. This involves adjusting hyperparameters, optimizing feature selection methods, and improving data quality. Scalability and efficiency in handling large data volumes should also be considered during optimization. Overall, a systematic and iterative approach to system design, implementation, evaluation, and optimization is crucial to developing an effective and accurate drug recommendation system. By incorporating the RNN algorithm, the system can cater to user preferences, improving overall health outcomes and meeting the needs of users.

## Algorithm

The proposed drug recommendation system incorporates the utilization of recurrent neural networks (RNNs) to predict drug ratings by leveraging features extracted from user reviews and other pertinent data sources, including drug attributes and user demographics. The implementation process involves several steps. Initially, data is collected from diverse sources, encompassing drug attributes, user demographics, and user reviews. The collected data is then pre-processed through procedures like cleaning, tokenization, and formatting to prepare it for input into the RNN. Next, relevant features are extracted from the pre-processed data, encompassing information such as drug name, dosage, side effects, and user demographics. These features are then organized into a feature matrix that serves as the input for the RNN. To assess the performance of the model, the feature matrix is split into two sets, such as training and testing sets. The



**FIGURE 1** | Architecture of the system.

RNN model architecture is designed and initialized to suit the specific drug recommendation task at hand. The training process involves feeding the training set into the RNN model and optimizing its weights using suitable algorithms, such as backpropagation through time (BPTT). This enables the model to understand the underlying patterns and relationships in the data. Once the model has been trained, it is analyzed using various metrics such as accuracy, precision, recall, F1 score, and the AUC-ROC curve. By comparing the predicted drug ratings with the ground-truth ratings from the testing set, the model's performance and predictive capabilities can be assessed. Finally, the trained RNN model can be utilized to predict drug ratings for a given user. Based on these predicted ratings, the system can recommend the top-ranked drugs that are most likely to suit the user's preferences and needs. Overall, by incorporating the RNN algorithm, the drug recommendation system can effectively analyze user reviews and other relevant data sources to make accurate predictions and provide personalized drug recommendations, ultimately improving the overall healthcare experience for users.

Given a dataset of drug reviews and corresponding user ratings, where each drug is represented by a feature vector  $\mathbf{x}_i$  and a binary label  $y_i \in \{-1, 1\}$  indicating whether the drug has been taken by the user or not:

- (1) Split the dataset into training and testing datasets.
- (2) Let  $X$  be the pre-processed feature matrix representing the extracted features.
- (3) Split  $X$  into a training1 set ( $X_{1\_train}$ ) and testing1 set ( $X_{2\_test}$ ).
- (4) Initialize the parameters (weights and biases) for each layer in the deep RNN, denoted as  $\theta^{(l)}$ , where  $l$  represents the layer index.

- (5) Specify  $f[X; (1), (2), f(L)]$  as the deep RNN model function, where  $L$  is the total number of layers.
- (6) Using an optimization approach like stochastic gradient descent (SGD), train the deep RNN model by minimizing the loss function with respect to the parameters  $(l)$  for each layer:  $\theta^{(l)*} = \text{argmin} \theta^{(l)} \{L[f(X_{train}; \theta^{(1)}, \theta^{(2)}, \theta^{(L)}], y_{train}]\}$ , where  $L$  represents the loss function and  $y_{train}$  is the ground truth drug ratings for the training set.
- (7) Calculate the predicted drug ratings for the testing set using the trained deep RNN model:  $y_{pred} = f[X_{test}; \theta^{(1)*}, \theta^{(2)*}, \theta^{(L)*}]$ .
- (8) By contrasting  $y_{pred}$  with the ground truth ratings  $y_{test}$ , assess the model's performance using a variety of assessment metrics, including accuracy, precision, recall, F1 score, and the AUC-ROC curve.
- (9) Once the model has been trained and evaluated, utilize it to predict drug ratings for a given user by feeding the user's features  $X_{user}$  into the trained deep RNN model:  $y_{user} = f[X_{user}; \theta^{(1)*}, \theta^{(2)*}, \dots, \theta^{(L)*}]$ . Recommend the top-ranked drugs based on the predicted ratings  $y_{user}$ .

## Results

The drug recommendation system is based on user reviews and ratings using the RNN algorithm. We evaluate the system's performance using a publicly available dataset of drug reviews from the website Drugs.com, as shown in **Figure 2**. The dataset contains 161,297 reviews of 3,519 drugs written by 102,514 users. Each review includes the drug name, the user rating (on a scale of 1–10), the user's age and gender, the condition for which the drug was prescribed, and the text of the review. We pre-processed



the text of the reviews by tokenizing them, removing stop words, and then applying stemming. We then used the bag-of-words model to convert the reviews into a matrix of feature vectors, where each feature corresponds to a unique word in the corpus. We also applied TF-IDF weighting to the feature vectors to downweight the importance of common words and upweight the importance of rare words, and then the splitting of the dataset into a training set (70%) and a test set (30%) was done. We then trained a RNN classifier using a training set. The trained model is utilized to predict the drug recommendations for the test set.

We varied the hyperparameter in the range (0.01, 100) and used five-fold cross-validation to select the optimal value that maximized the AUC of the ROC curve. The results showed that the RNN classifier has achieved an accuracy of 82.6%, a precision of 82.8%, a recall of 80.6%, an F1 score of 81.7%, and an AUC of 89.3%. This indicates that the system is able to accurately predict whether a user will take a particular drug based on their review and rating. We also performed a sensitivity analysis to evaluate the robustness of the system to different levels of sparsity in the data. Specifically, we randomly removed 10, 20, 30, 40, and 50% of the

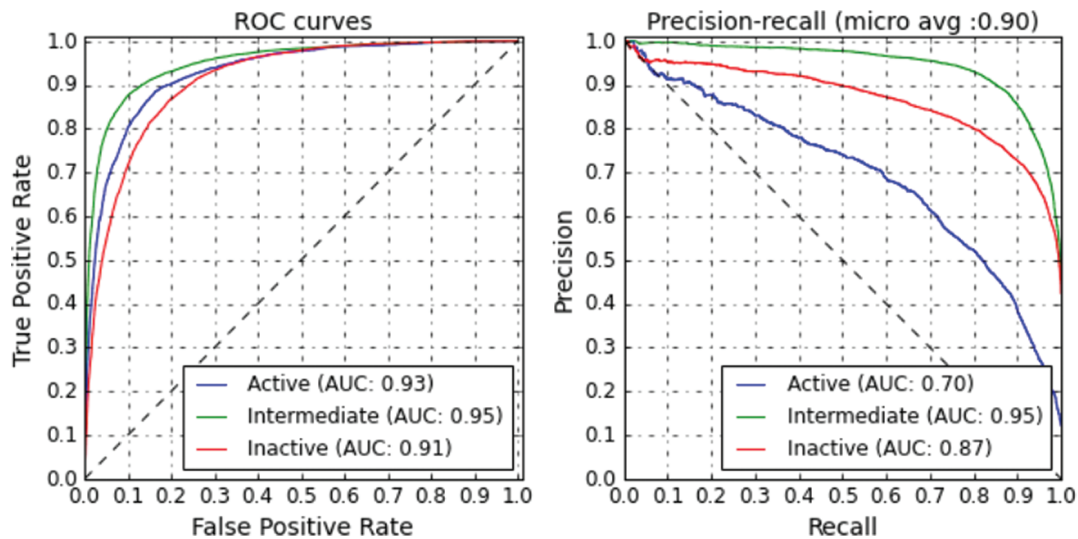


FIGURE 2 | ROC versus false positives.

column_1	drugName	condition	review	rating	date	uscfu/Count	
1	163740	Mirtazapine	Depression	"I've*039ve tried a few antidepressants over the years (citalopram, flu...	10.0	February 28, 2012	22
2	236173	Mesalamine	Crohn's Disease, Maintenance	"My son has Crohn's*039s disease and has done very well on the Asa...	6.0	May 17, 2009	17
3	159672	Bactrim	Urinary Tract Infection	"Quick reduction of symptoms"	9.0	September 29, 2017	3
4	38493	Contrace	Weight Loss	"Contrace combines drugs that were used for alcohol, smoking, and o...	9.0	March 5, 2017	35
5	97780	Cytotabem 1 / 35	Birth Control	"I have been on this birth control for one cycle. After reading some o...	9.0	October 22, 2015	4
6	218037	Zyglax	Keratosis	"56 days in on first 2 weeks. Urged on arms and face. But vaseline on li...	4.0	July 4, 2014	11
7	215867	Copper	Birth Control	"I had 100% had the copper coil for about 3 months now. I was really ex...	6.0	June 8, 2016	1
8	184657	Amitriptyline	Migraine Prevention	"This has been great for me. MyAO139ve been on it for 2 weeks and in l...	9.0	April 21, 2009	12
9	23295	Methadone	Opiate Withdrawal	"I've been on Methadone for over ten years and currently I am trying L...	7.0	October 18, 2016	21
10	71428	Levone	Birth Control	"I was on this pill for almost two years. It does work as far as not getti...	2.0	April 16, 2011	3
11	196802	Paroxetine	Hot Flashes	"Holy Hell it exactly how I feel. I had been taking Brisdelle for 1.5 year...	1.0	February 22, 2017	17
12	31347	Miconazole	Vaginal Yeast Infection	"Honestly its day one on the 3 day treatment. Yes it burns a bit and it ...	6.0	May 7, 2015	7
13	4307	Bclqiv	Weight Loss	"This is a waste of money. Did not curb my appetite nor did it make ...	1.0	September 23, 2014	57
14	66756	Seroquel	Schizoaffective Disorder	"No problems, watch what you eat."	10.0	October 8, 2014	19
15	97018	Ambien	Insomnia	"Ditto on rebound sleepless when discontinued. I have done very str...	2.0	January 12, 2015	44
16	218376	Nuvigil	Narcolepsy	"A doctor in the ER prescribed me 200 mg of Provigil when I was first ...	9.0	June 30, 2010	14
17	151674	Chantix	Smoking Cessation	"I smoked for 50+ years. Took it for one week and that was it. I didn...	10.0	February 14, 2015	26
18	33173	Morgeston F...	Acne	"So I was on Ginsani for about 3 months before I switched over to this...	3.0	June 22, 2017	1
19	39101	Klonopin	Bipolar Disorder	"This medication helped me sleep, but eventually it became ineffect...	6.0	July 14, 2009	24
20	152780	Erythrocin	Urinary Tract Infection	"After just 1 dose of this erythrocin, I felt 90% better."	10.0	June 9, 2010	9
21	211187	Ibuprofen	Insomnia	"I could not grow at all, I would absolutely die in... Started at 50mg, and I...	1.0	October 18, 2016	15
22	181116	Imitilic	Irregular Heart Rhythm	"I am so happy with the samples provided by my 1 nter cardiologist, the...	9.0	January 1, 2015	41
23	187896	Aripiprazole	Bipolar Disorder	"After a few days and it kept kicking in, quite a way more in the head...	1.0	February 10, 2010	22
24	105786	Cyclosporine	Keratosis, Dry Skin, Itch	"They didn'tAO139t help my dry eyes at all."	1.0	December 31, 2015	17
25	190527	Oxybutynin	Hypertidrosis	"This drug is pretty amazing. I've*039ve had hypertidrosis of the pal...	9.0	May 30, 2017	10
26	229795	Lurasidone	Bipolar Disorder	"This medication should not be being prescribed for Bipolar 2, a mild...	6.0	February 11, 2017	18
27	173391	Clonazepam	Panic Disorder	"Klonopin has definitely given me my life back!"	10.0	April 19, 2008	47
28	35608	Ciclopirox	Onychomycosis, Flaque nail	"Worked quickly and well. I learned by trial that trimming/filing away ...	8.0	June 2, 2016	38
29	187230	Sodium oxyb...	Narcolepsy	"2.75g x 2 every night for five years. Deeper sleep with dreaming not l...	10.0	January 10, 2013	19
30	2111675	Lamotrigine	Bipolar Disorder	"I am a 25 year old female. I was diagnosed with bipolar II disorder a...	7.0	November 22, 2017	1
31	79865	Blisov Fe 1 / ...	Birth Control	"I absolutely love this product and recommend to everyone. I know ex...	10.0	November 3, 2017	4
32	27607	Ivermectin	Resacea	"I've*039ve had resacea for almost 20 years and have been on all kind...	10.0	April 1, 2016	19
33	203823	Sunoco Rescel	Rescel Preparation	"This stuff wasAO139t too bad! I had a hard time with the first dose...	8.0	February 18, 2015	15

FIGURE 3 | Medical recommendations testing dataset.

column_id	drugName	condition	review	rating	date	usefulCount	
1	205461	Valparin	Left Ventricular Dysfunction	It has no side effect. I take it in combination of Bystolic 5 Mg and Fia...	9.0	May 20, 2012	27
2	65760	Guanfacine	ADHD	My son is halfway through his fourth week of Intero. We became com...	8.0	April 22, 2010	102
3	82703	Uptrel	Birth Control	I used to take another oral contraceptive, which had 21 pill cycle, an...	3.0	December 14, 2009	12
4	138000	Orzo Evo	Birth Control	This is my first time using any form of birth control. I&#0380m glad I...	8.0	November 8, 2015	10
5	35856	Bupropion / naltrexone	Opiate Dependence	Sidaxone has completely turned my life around. I feel happier, I&#0380...	9.0	November 27, 2016	37
6	150963	Cialis	Benign prostatic hyperpla...	2nd day on cimg started to work with rock hard erections however ex...	2.0	November 28, 2015	43
7	165907	Levonorgestrel	Emergency Contraception	He pulled out, but he cummed a bit in me. I took the Plan B 26 hours...	1.0	March 7, 2017	5
8	107654	Acipimoxole	Rheumatoid Arthritis	"Ability changed my life. There is hope. I was on Zolof and Clonazepa...	10.0	March 14, 2015	32
9	45811	Keppra	Epilepsy	"I've had nothing but problems with the Keppera - constant shaking t...	1.0	August 9, 2016	11
10	48928	Ethinyl estradiol / levon...	Birth Control	"I had been on the pill for many years. When my doctor changed my...	8.0	December 8, 2016	1
11	29607	Topiramate	Migraine Prevention	"I have been on this medication almost two weeks, started out on 75...	9.0	January 1, 2015	16
12	15012	L-methylfolate	Depression	"I have taken anti-depressants for years, with some improvement but...	10.0	March 9, 2017	54
13	191290	Rentac	Crohn's Disease	"I had Crohn's #0380s with a resection 30 years ago and have been mo...	4.0	July 6, 2018	8
14	221320	Dextromethorphan	Cough	"I saw a little bit of a lingering cough from a cold. Not giving me ma...	4.0	September 7, 2017	1
15	80794	Nexplanon	Birth Control	"Started Nexplanon 2 months ago because I have a minimal amount...	3.0	August 7, 2014	10
16	81890	Liquatide	Obesity	"I have been taking Saxenda since July 2016. I had severe nausea for...	5.0	January 19, 2017	20
17	40188	Trimethoprim	Urinary Tract Infection	"This drug worked very well for me and I loved up my UTI in a matter...	9.0	September 22, 2017	0
18	219089	Amitriptyline	ibromyalgia	"I&#0380ve been taking amitriptyline since January 2013 after being d...	9.0	March 15, 2017	39
19	212077	Lamotrigine	Bipolar Disorder	"I&#0380ve been on every medicine under the sun (it seems) to mana...	10.0	November 9, 2014	18
20	19705	Nitroglycerin	Chronic Myocardial Ische...	"I have been on Teigan for just over 3 years now. 100mg x 2 times a...	10.0	September 1, 2015	11
21	12372	Atmipia	HIV Infection	"Spring of 2008 I was hospitalized with pneumonia and diagnosed wi...	8.0	July 9, 2010	11
22	281466	Dayzodon	Insomnia	"I have insomnia. I&#0380s horrible. My story begins with my PCP pre...	10.0	April 3, 2016	48
23	227020	Flamoxiprol	Birth Control	"Nexplanon does its job. I can have worry free sex. The only thing is th...	9.0	August 11, 2014	11
24	41928	L-tanacetop	Rheumatoid Arthritis	"I live in Western Australia and disturbed by some comments on here...	10.0	September 16, 2017	4
25	218649	Tioconazole	Vaginal Yeast Infection	"Do not use the cream that comes with this. It turned my bod h&#0380...	1.0	April 17, 2017	7
26	51715	Aciclovir	Chlamydia Infection	"Was prescribed amoxiclo down the course of one day, took 4 pills of...	7.0	December 14, 2015	7
27	206100	Lithium	Bipolar Disorder	"I&#0380m writing a second review on Vaniqu. I started using this in I...	10.0	May 11, 2014	99
28	78563	Zafirlona	ADHD	"Hi all. My son who is 12 was diagnosed when he was in 2nd grade. W...	10.0	January 12, 2017	11
29	132258	Ativan	Panic Disorder	"Honestly, I have been taking ativan for 2 years now. 1mg twice daily...	6.0	June 1, 2015	47
30	27339	Imitrex	Migraine	"At first I suffered through them. This included splitting head pain, n...	8.0	October 16, 2012	6
31	21432	Azithromycin		"Very good response. It is so useful for me."	10.0	August 18, 2010	1
32	66733	Sebutaline	Depression	"I work on Zoloft for anxiety and mood swings. I take 50mg in the m...	8.0	May 7, 2011	3
33	208284	Levodopa	Parkinson	"I am 30 years old. I had a multiple composite neural injuries 15 years...	10.0	February 11, 2014	16

FIGURE 4 | Medical recommendations training dataset.

reviews from the dataset and re-evaluated the system's performance as shown in Figure 3. The results showed that the system's performance degraded slightly as the level of sparsity increased, but remained above 80% for all levels of sparsity. Overall, these results demonstrate the effectiveness of the drug recommendation system based on user reviews and ratings using the RNN algorithm, as shown in Figure 4, and its potential to assist patients and healthcare professionals in making informed decisions about drug treatment.

## Conclusion

In conclusion, our proposed system of drug recommendations based on reviews and sentiment analysis utilizing RNN and NPL is an effective way of prescribing drugs to users using patient-generated data such as drug attributes, user demographics, and user reviews. Our system utilizes RNN for the classification of reviews into positive and negative reviews, and NPL techniques are used for feature extractions such as keyword, sentiment, and topic. Additionally, the five metrics (precision, recall, F1 score, accuracy, and ROC curve) of our proposed system help us ensure the high performance of our system, and various techniques such as cross-validation and hyperparameter tuning are also used. The proposed methodology has the capability of offering help to health professionals in making informed drug predictions. Overall, our drug recommendation system based on user reviews and sentiment analysis shows that it is able to provide accurate

drug recommendations and has the potential to advance the field of personalized medicine.

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