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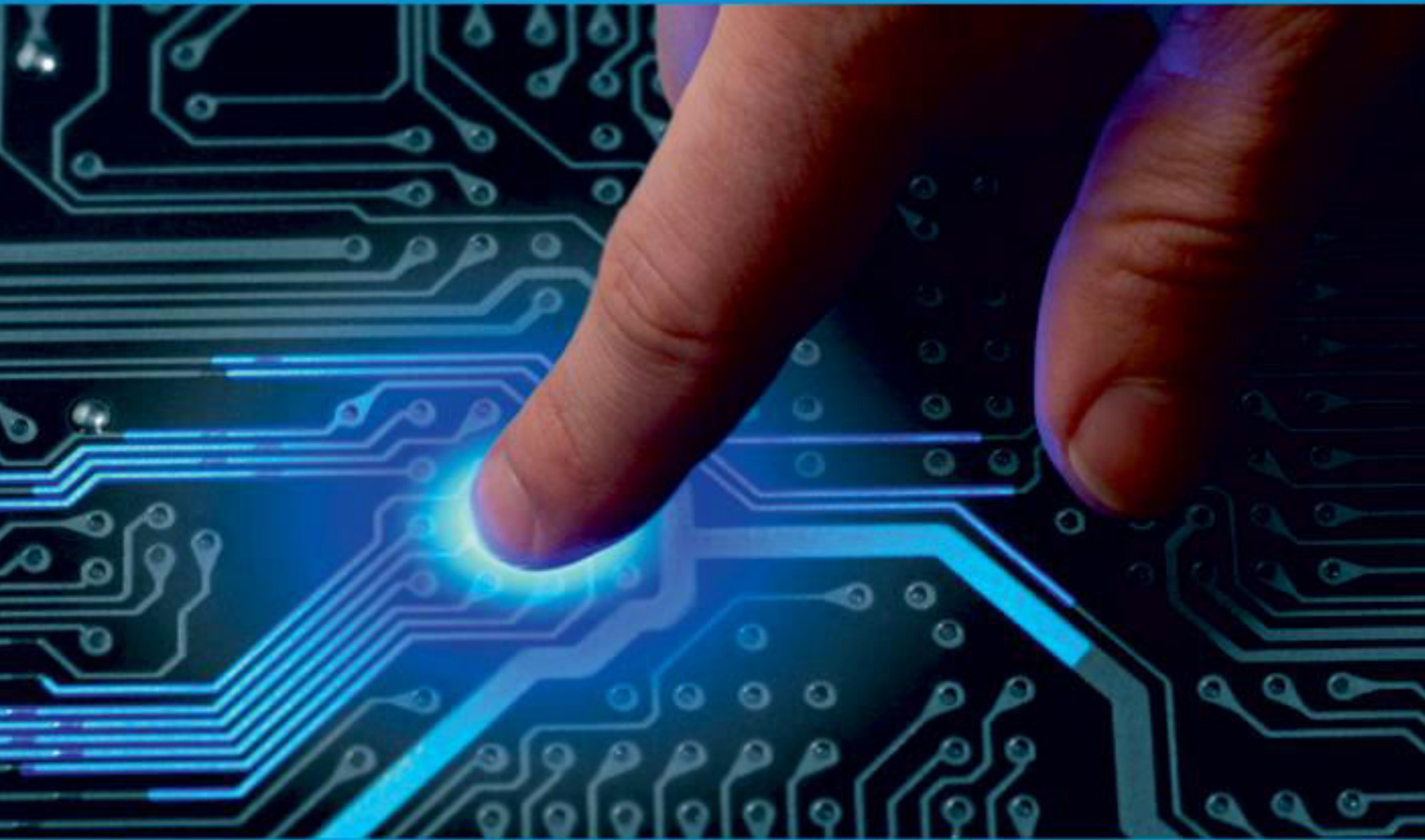

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Panacea: An Intelligent Medicine Recommendation System

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ABSTRACT: A recommendation system may help the user make sense of all the available data and come up with well-considered suggestions. User-generated material is conveyed in human language in a variety of nuanced ways, making it difficult to provide recommendations based on a study of attitudes. Research in the sphere of health and medicine has lagged behind those of more mainstream areas like consumer electronics, movies, and eateries. There may be significant insight on where to put our attention to improve public health, and what choice to make, that may be gleaned by analyzing people's sentiments about their healthcare experiences and their personal interactions with drugs. In this project, I developed a framework for a medicine recommender system that makes use of sentiment analysis techniques to analyze user feedback on various pharmaceutical products. They are more aware of the need of maintaining a healthy lifestyle, and as a result, the majority of people enjoy a long and healthy lifespan. However, numerous studies demonstrate that a significant number of individuals lose their lives as a result of medical mistakes related to the inappropriate dosages or types of medications being prescribed. These technologies, which are similar to machine learning, deep learning, and data mining, are always improving and may help us better understand our medical past and minimize the occurrence of medical mistakes since they are designed with doctors in mind. The recommendation score is improved by taking into account the opinions of the general public and the number of times such opinions were helpful. Two deep learning algorithms, the A.N.N. (Artificial Neural Network) and L.S.T.M., were employed to determine sentiment ratings (Long Short-Term Memory). On the other side, we use the LGBM (Light Gradient Boosting Machine) classifier to discover practical count values. Predicted thoughts were evaluated using tools including accuracy score, recall, f1-score, confusion matrix, precision. Analysis is performed to fine-tune the parameters of each algorithm for optimal performance.

KEYWORDS: Drug, Machine Learning, NLP, Smote, Bow, TF-IDF, Word2Vec, Sentiment evaluation, Recommendation Engine.

I. INTRODUCTION

Patients often struggle to find a doctor they can trust during a medical crisis, and their overall health and happiness can be greatly impacted by this uncertainty. To address this issue, clinical studies and established methods are used to determine the safety of medicines. One promising solution is to use post-marketing drug monitoring techniques, such as drug review analysis, to keep track of medication-related problems. By using text mining on drug reviews, patients can make informed decisions about their prescriptions, while doctors and pharmacies can reduce medication errors and gain valuable insights from the public's perspective.

Data mining and recommender systems have advanced to the point where they can analyze past diagnoses and drug user feedback to determine the best course of treatment, which can greatly reduce harmful prescription mistakes. However, the abundance of medical information available online makes it difficult for consumers to find relevant information that can improve their health. To help close this information gap and aid in healthcare decision-making for both patients and doctors, a medication recommendation system has been developed.

Previous research has primarily focused on rating expectations and suggestions in the e-commerce industry, but few studies have been conducted in the medical field. To help doctors and patients learn more about the effects of medications for certain diseases, a medication recommendation framework is crucial. This framework uses consumer surveys to categorize responses and provide tailored recommendations, and utilizes sentiment analysis and feature engineering to determine under what circumstances to prescribe medication. Sentiment analysis is a set of techniques

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for parsing text for underlying emotional meanings and then using that information to form conclusions about the author's intentions.

Recommender systems are widely used in data science and have been implemented by many major IT firms, such as Amazon, YouTube, and Facebook. Our research focuses on opinion mining in drug reviews, where people discuss their reactions to different medications and rate how helpful they were. When implemented, the suggested method of sentiment analysis would benefit not only patients, but also pharmacists and physicians by providing them with helpful summaries of public opinion.

While clinical trials and other predetermined processes are used to assess a medical product's potential risks and benefits, it is possible that harmful pharmacological effects and hazards will not be discovered until after the medicine has hit the market. The goal of this project is to create and implement a medication recommendation system that uses a variety of data mining tools. By combining information from different sources, we are using various prediction algorithms along with natural language processing for sentiment analysis and recommendations. The rest of the report will discuss the data gathering, pre-processing, methodology, implementation, results, and conclusion of our project.

II. RELATED WORK

Due to the sharp rise in corona virus cases, there is a global shortage of doctors, particularly in rural areas where there are fewer specialists than in urban ones. The education required to become a doctor must be completed in six to twelve semesters. As a result, increasing the number of doctors in a short amount of time is impossible. Under this challenging moment, a Telemedicine platform needs to still be powered up as much as feasible [1].

A diverse committee carried practical methodical evaluations of the pertinent literature and used the Ranking of Judgments, Appraisal, Adaptation, and Functional traits for therapeutic advice. This group created and supported guidelines on particular diagnostic and therapeutic approaches for elderly patients experiencing community-acquired pneumonia. The article doesn't discuss pneumonia mitigation or pre-symptomatic diagnosis parameters [2].

There are quite lot of patient testimonials of medications online. In relation to medicine identification, this report offers a succinct outline on attribute mined methodologies. Again for healthcare companies, timely screening of negative chemical effects is a key area of investigation. It is difficult to extract important ideas through brief, chaotic evaluations. The probabilistic aspect mining model (PAMM) is suggested as a solution to this issue in order to find the sides and subjects related to category labeling. Owing to a special characteristic of PAMM, it concentrates on identifying factors specific to a single type instead of simultaneously finding qualities over all categories during per iteration. The characteristics discovered also possess the quality of being class differentiating, which implies they may be utilised to set one class apart from another. The likelihood of components resulting mostly from blending of notions from other classes is decreased, making it simpler for individuals to understand the discovered aspects. [3].

The report [4] presents GalenOWL, as semantic-enabled virtual structure, to assist professionals in learning more about the medications. The study presents a paradigm that recommends drugs to a user based on their condition, tolerances, and medication problems. Medical data and nomenclature were ontologically translated utilizing international standards like ICD-10 and UNII, and then correctly matched using biomedical parameters for GalenOWL.

III. PROPOSED METHODOLOGY

The UCI ML repository's Drug Review DatasetDrugs.com) was used as the source of the dataset for this study [4]. This dataset has six attributes: the name of the drug used (text), the review of the patient, the patient's condition, the useful count (numerical), the date (date) of the review entry, and a 10-star patient evaluation (numerical) indicating the level of satisfaction with the treatment overall. There are 215063 incidents in all. The proposed model for creating a system that recommends medications is depicted in Fig. 1. Data preprocessing, categorization, evaluation, and recommendation are the four processes that make up this process.

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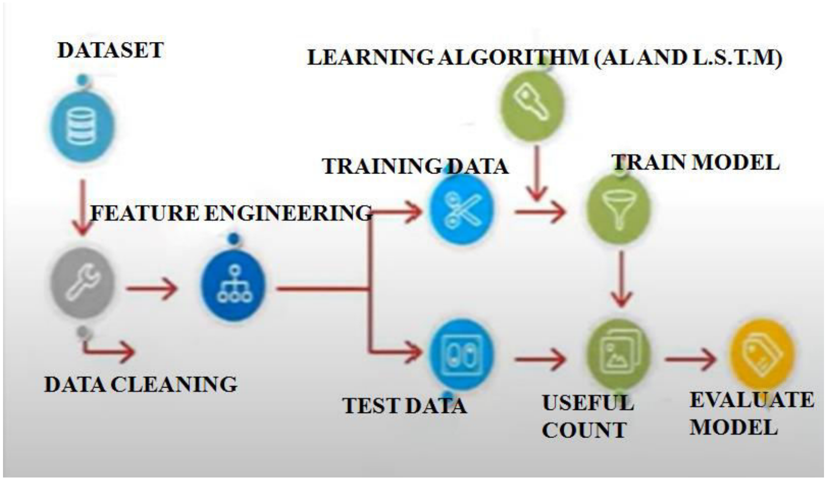

Figure 1. Proposed Drug Recommendation System

LSTM ALGORITHM

Long Short Term Memory Nets, least frequently used as "LSTMs," are one special type of RNN that would identify lengthy correlations. Elements were initially introduced by Hochreiter & Schmidhuber (1997), and several scientists expanded and made them prominent in later studies. These are extensively utilized and excel tremendously enough being administered with a broad spectrum of problems. LSTMs were purposefully developed to combat the dilemma of protracted dependency. Individuals wouldn't try hard to acquire; rather, linking back for a prolonged time span of duration is essentially its baseline behavior.

Many recurrent neural networks do resemble a set of neural network units in form that loop. Every chain-like design in traditional RNNs will include an architecture that is quite simple to comprehend, such a solo lower tier. Even while the recurring module of LSTMs often has a topology similar to a chain, it is formed differently. Instead of only having one layer, there will be four, and they will join in a really novel way.

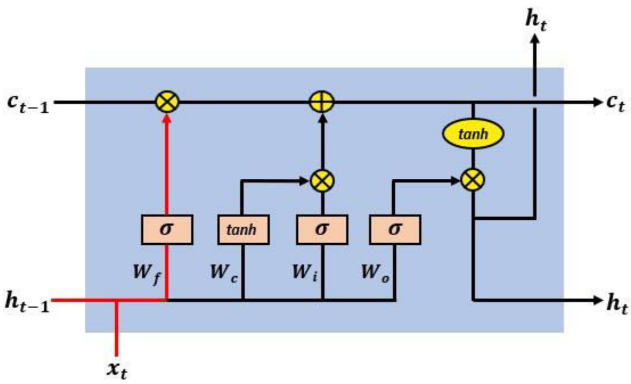

Figure-2 LSTM Structure

Although it too has a chain-like architecture, the repeating component of LSTMs is organised differently. Rather than just one, there are four layers in the neural network, and they interact significantly differently.

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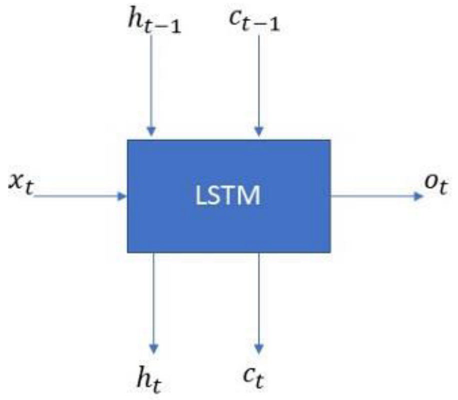


$$f_t = \sigma_g\ (W_f \times\ x_t + U_f \times h_{t-1} + b_f)$$
$$i_t = \sigma_g\ (W_i \times\ x_t + U_i \times h_{t-1} + b_i)$$
$$o_t = \sigma_g\ (W_o \times\ x_t + U_o \times h_{t-1} + b_o)$$
$$c'_t = \sigma_c\ (W_c \times\ x_t + U_c \times h_{t-1} + b_c)$$
$$c_t = f_t \cdot c_{t-1} + i_t \cdot c'_t$$
$$h_t = o_t \cdot \sigma_c(c_t)$$

σ_g : *sigmoid*
σ_c : tanh
. : element wise multiplication

f_t *is the forget gate*
i_t *is the input gate*
o_t *is the output gate*
c_t *is the cell state*
h_t *is the hidden state*

The diagram below shows how each line moves a whole vectors from one data type output to someone else's input. While the pink circles represent point - wise operations such vector addition, the yellow boxes represent learned neural network layers. Lines that merge together suggest concatenation, whereas a forked line shows that content has been duplicated and is being transmitted to other locations.

ANN ALGORITHM

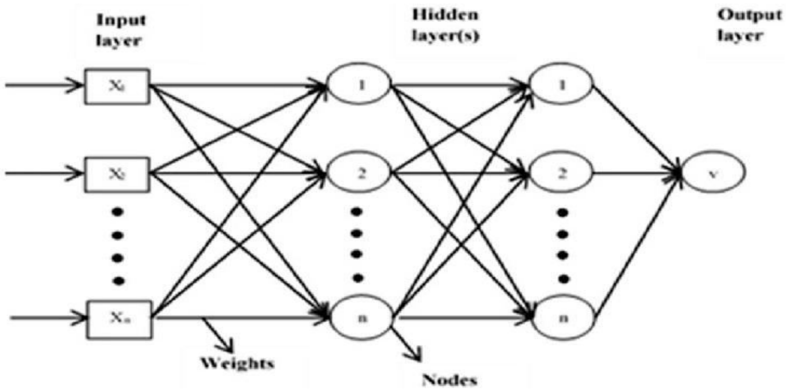
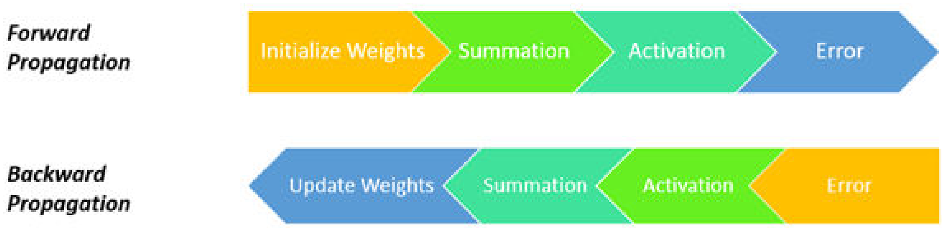


Figure-3 ANN Framework

Artificial neural networks (ANNs) are attempts to mimic a network of neurons that comprise the human brain in order to enable the computer to comprehend things & make judgements in a manner that is comparable to that of a person. Standard computers are programmed to behave as networked brain cells to create ANNs.
In neural networks, lowering the error will be our primary objective. To make this happen, all of the weights must be updated using back propagation. Finding a weight adjustment that will result in the least amount of inaccuracy is necessary. Therefore, we determine dE/dW1 and dE/dW2.



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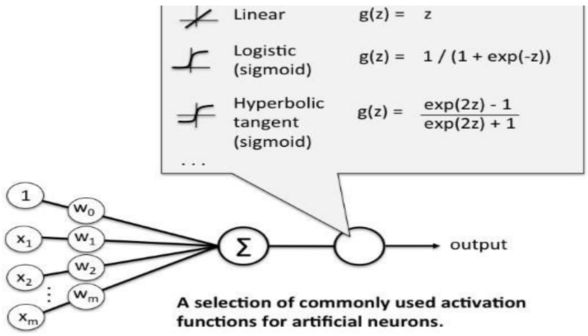
Our following step will be to update the weights using the gradient descent process once you have determined changes in weights regarding error. Please review additional information about gradient descent.

$$W1new = W1old - \eta \frac{dE}{dW1}$$

$$W2new = W2old - \eta \frac{dE}{dW2}$$



This context for real-world situations cannot be understood by computers in the same way that it can by human brains. Artificial neural network were initially developed in the 1950s to address this issue. Artificial neural networks (ANNs) are attempts to mimic the network interconnected neurons that comprise the human brain in order to enable the computer to understand things and render judgements in a manner that is comparable to that of a person. Programming common computers to behave as networked brain cells is required to create ANNs.

Artificial neural networks (ANNs) and connectionist systems are computer architectures that have some similarities to the organic neural networks seen in animal brains. Such systems often lack any task-specific rules and instead "learn" to accomplish tasks by taking into consideration instances.

IV. RESULT AND ANALYSIS

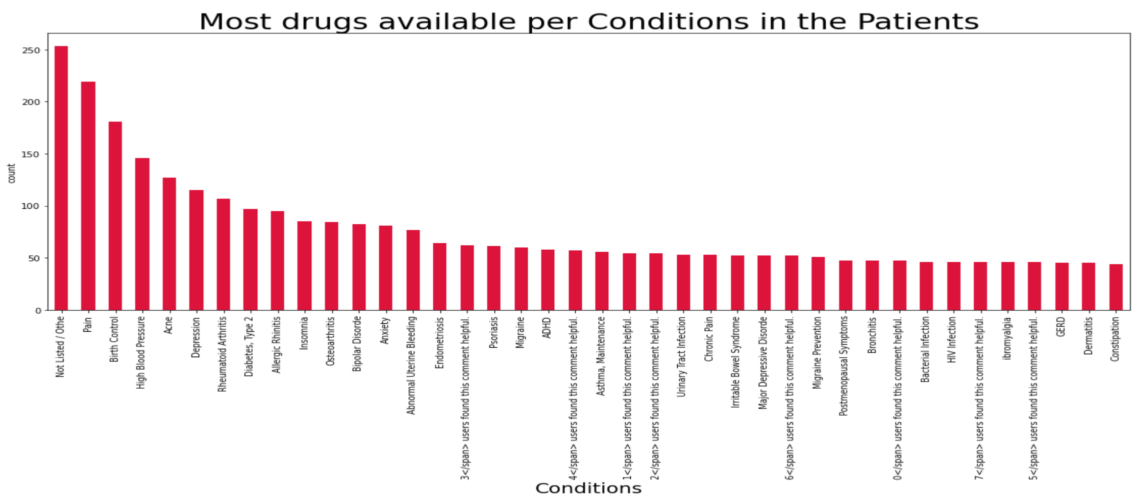


Figure4most drugs available per conditions

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In ***Figure4*** bar chart shows available distinct drugs with counts from our dataset. For pain, birth control, and high blood pressure we have a greater number of records in our dataset.

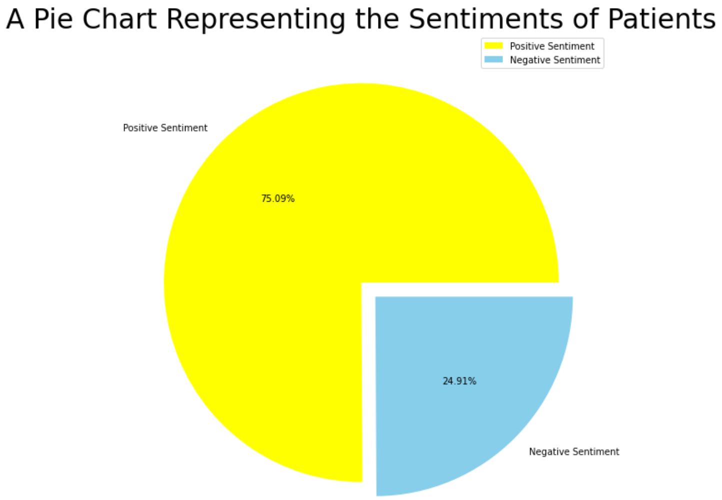

Figure5Percentage of Records Positive Vs Negative

In ***Figure5***pie chart looks like this. The proportion of records with positive sentiment and the percentage of records with negative sentiment from our review feature are shown below for 100%. We can see from the graphic that our review function has more positive sentiment records than negative sentiment records.

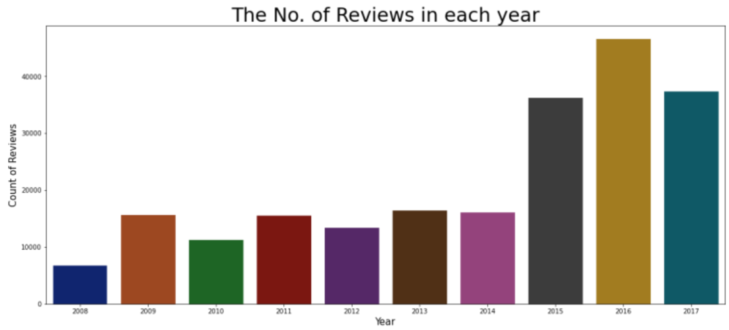

Figure6 Record count for each season

The number of records gathered during each year is depicted in the bar graph top***Figure 6***. More entries were gathered in 2016 than in any other years. Fewer statistics were gathered in 2008 than in previous years

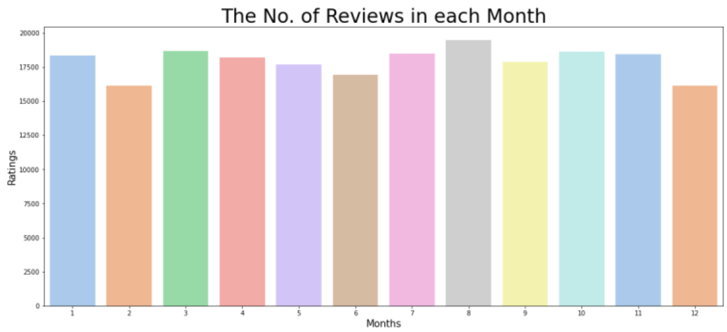

Figure-7 Number of records in each month

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In ***Figure-7*** bar-chart shown above shows how many records have been collected to our dataset on average per month.

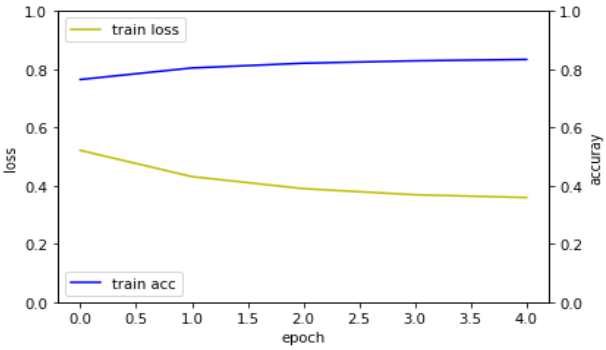

Figure8 Accuracy and loss plot of artificial neural network

The increase in accuracy and decrease in loss after training are depicted in the above graph***Figure 8***. The Matoplotlib package and information acquired from model-trained historical data were used to create these displays.

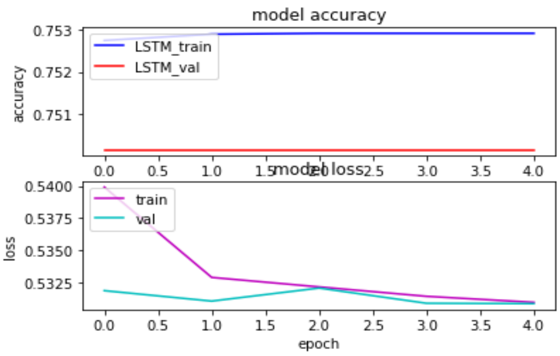

Figure9Accuracy and Loss plots of Long-short term memory

When the long-short-term memory model is trained, the accuracy and loss are shown to grow and decrease, respectively, in the two sub-plots above**Figure 9**. Here, the first figure shows training and validated accuracy, and the second plot shows training and validated loss.

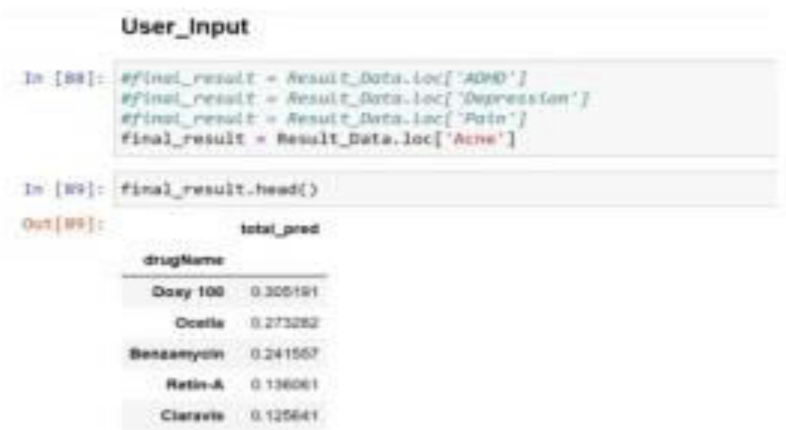

Figure10 Recommended Drugs Sample Result

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The above*Figure 10* screenshot of a Data frame is the final result of the drug recommendation project work. It looks at some input conditions (diseases) from the user and suggests top drugs with recommendation scores based on sentiments and useful counts.We can see the artificial neural network model structure employed in our project work in the figure up top. With the help of the layers Dense, Batch Normalization, Activation, and Dropout, this artificial neural network model was thoroughly developed. The final activation method is sigmoid activation. For comparative purposes, the long-short term memory model was adopted in this experiment. This design uses Embedding, LSTM, Dropout, and Dense layers to create its structure. The usage of dropout layers helps avoid overfitting.We have developed a function called review to words for text cleaning. In this function, we removed HTML elements, numerous white spaces, converted uppercase letters to lowercase letters, removed stop words, and then stemmed the text. Later, when we wanted to clean the review feature from our dataset, we ran this method.

DATASET:

	uniqueID	drugName	condition	review	rating	date	usefulCount
0	206461	Valsartan	Left Ventricular Dysfunction	"It has no side effect, I take it in combinati...	9	20-May-12	27
1	95260	Guanfacine	ADHD	"My son is halfway through his fourth week of ...	8	27-Apr-10	192
2	92703	Lybrel	Birth Control	"I used to take another oral contraceptive, wh...	5	14-Dec-09	17
3	138000	Ortho Evra	Birth Control	"This is my first time using any form of birth...	8	3-Nov-15	10
4	35696	Buprenorphine / naloxone	Opiate Dependence	"Suboxone has completely turned my life around...	9	27-Nov-16	37

The dataset utilized in our study is depicted in the figure above. It has seven characteristics. The task was finished using a categorization idea. Review is treated as an independent element in this case, whereas rating is treated as a dependent feature.

V. CONCLUSION

In this study, we implemented a drug recommendation system using two deep learning algorithms: an artificial neural network and a LGBM classifier. The artificial neural network achieved an impressive accuracy rate of 99%, while the LGBM classifier had a loss of 0.32. By combining the probabilities obtained from the sentiment analysis and useful count prediction performed by the artificial neural network, we were able to calculate a suggestion score for each drug based on the condition. This approach utilizes people's opinions to provide trustworthy outputs and replicate their suggestions. To achieve this, we utilized the Tensorflow library for various natural language processing tasks such as vectorization, dimensionality fixing, and algorithm usage. This work aims to assist physicians and patients in making informed decisions about the most appropriate drug for a given condition. Overall, the results of this study demonstrate that our drug recommendation system is a reliable and effective tool for helping people makes informed decisions about their healthcare.

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