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Dynamic Discovering and Modelling Drug Recommendation System using LSTM

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ABSTRACT
Drug recommendation systems have become increasingly important in healthcare, as they assist physicians in making informed decisions regarding medication for patients. With the rapid advancement of machine learning techniques, there has been a surge of interest in developing drug recommendation systems that can learn from large-scale medical data. In this study, we propose a novel drug recommendation system that utilizes Long Short-Term Memory (LSTM) to discover and model the drug prescription patterns in a dynamic manner. The proposed system is designed to learn from patients' medical records, drug prescriptions, and other relevant data, to provide personalized drug recommendations for individual patients. The LSTM-based model captures the sequential dependencies between patients' medical history and drug prescription patterns, allowing the system to adapt to changes in patients' medical conditions over time. The system takes into account various factors such as age, gender, medical history, and other relevant information, to provide accurate and personalized drug recommendations. We have used the real-world dataset made up of patient medical records and prescription data to assess the accuracy of the suggested method. The system is capable of adapting to changes in patients' medical conditions over time, ensuring that the recommendations provided are always accurate and up-to-date. The system has the potential to revolutionize the healthcare industry by providing personalized drug recommendations that can significantly improve patient outcomes.
Keywords— Recommendation system, NLP, Machine Learning, LSTM

I. INTRODUCTION

The medical studies nowadays increasingly rely on unconventional information sources to get relevant information about health conditions, the effectiveness of treatments, side effects, drug interactions, and other aspects. One such source of information can come from drug users themselves in the form of user-generated texts such as free-text site reviews, social media posts, and other texts. For example, these sources have been used successfully to track adverse drug reactions (ADRs), allowing researchers to identify uncommon and underreported ADRs by monitoring users' complaints about their health on social media or in specialized forums. Before there were online reviews, people would ask around for advice on a product's reputation or quality. This kind of research take a lot of days or months and frequently was wholly ineffective. Thankfully,

there are now millions of reviews available online across numerous platforms. Online reviews offer readers insightful perspectives and real-world experiences with products and services, as well as information about the features of the products. Customers who read the evaluations will therefore utilise them as resources and make more informed decisions. Reviews of a company's goods or services are frequently used by the company to enhance the goods or services. It is made clear that both viewers and producers gain by assessing how useful reviews can be for them. Spool said that by posing the query "Was this review helpful to you?" and using the responses, websites like Amazon.com can highlight the reviews that are the most beneficial.
The same is true for pharmaceutical companies and patients who will find drug reviews useful. Patients will save time and have a better understanding of both therapeutic and adverse effects by specifically reading an excellent and informative drug review. This study so focuses on this region and aids in determining how accurate helpfulness prediction is.
Health-related social networks have grown quickly during the past few years. Many online drug reviews have become a new open source for gathering healthcare data. On a variety of healthcare and drug related website like AskaPatient and Drugratingz, enormous amounts of drug reviews are created and published quickly. These reviews include first-hand user experiences and drug reactions, and they also benefit from expressing patients' genuine voices and experiences using drugs. In addition, viewers of reviews have the option of voting for the reviews if they feel that they offer them helpful advice and engaging product experiences.
These reviews include first-hand user experiences and drug reactions, and they also benefit from representing the real opinions and feelings of patients regarding the medications. In addition, viewers of reviews have the option of voting for the reviews if they feel that they offer them helpful advice and engaging product experiences.
NLP is incredibly important to the machine learning business. The analysis of medical reviews and through the texts, it plays a significant role in the field of medical healthcare in particular. The need for a perfect machine learning algorithm that makes predictions with zero errors persists indefinitely. We intended to evaluate the application of NLP algorithms, particularly Sentiment Analysis, thus we decided to use a data set that is more comparable to the medical healthcare sector for our study.
The drug recommendation system has the potential to revolutionize the healthcare industry by providing personalized drug recommendations that can significantly improve patient outcomes. This approach can lower the possibility of negative drug responses and interactions, as well as guarantee that patients receive the best treatments possible for their health conditions.

II. EXISTING SYSTEM

Most of the drug recommendation algorithms in use today are static and do not take into consideration how dynamic drug prescription patterns are. As a result, especially for patients with complicated medical conditions, they might not offer precise and individualised recommendations. Additionally, many of the current drug recommendation systems use rule-based systems, which might not be able to fully account for the intricate connections between patients' medical histories, prescription drug trends, and other pertinent data.
In order to solve the shortcomings of the current drug recommendation systems, numerous studies have been carried out. For instance, some researches have suggested employing data mining techniques to identify trends in patient medical histories and drug prescription patterns as well as connections between these patterns.

Recently, there has been a growing interest in utilizing Long Short-Term Memory (LSTM) to discover and model the dynamic nature of drug prescription patterns. LSTM is a type of artificial neural network that is capable of capturing sequential dependencies in data, which makes it ideal for modelling drug prescription patterns. Several studies have shown the effectiveness of LSTM-based models in drug recommendation systems. For example, a study conducted by (Guo, 2019) proposed an LSTM-based model that utilizes patients' medical records and drug prescription patterns to provide personalized drug recommendations. The study demonstrated the effectiveness of the proposed model in providing accurate and personalized drug recommendations.

(Jin, 2020) hybrid recommendation system was suggested in another study. It combines LSTM and matrix factorization techniques. To make personalised drug recommendations, the proposed system makes use of patient medical records, drug prescription trends, and information on drug-drug interactions. The study proved how well the suggested system works at giving precise and personalised medicine recommendations.

(Eysha Saad, 2021) This paper addresses the issue of domain- specific sentiment lexicons and the manual annotation needed in a learning-based approach to user sentiment analysis. For labelling and classication, it combines lexicon-based and learning-based methodologies to achieve this. The efficacy of TextBlob, VADER, and AFFIN as a data annotation strategy for drug reviews is assessed. According to experimental analysis, TextBlob typically produces superior outcomes when annotating drug reviews. On the annotated data, two conventional approaches—TF and TF-IDF—and one modified approach—TF and TF-IDF combined—are used for feature extraction.

(Marco Viceconti, 2021) A consensus process that resulted in a taxonomy for In Silico Trials CoUs and a list of 46 potential CoUs that cover every category of the proposed taxonomy was summarised in this review paper. The authors think that the first crucial stage in the establishment of Good Simulation Practise for In Silico Trials is reaching an agreement on potential Contexts of Use, such as the one here. A list like this makes it possible to have talks about the regulatory science underpinning in silico trials that are based on a concrete range of use cases. For both technical and cultural considerations, creating a Good Simulation Practise standard is a difficult task.

(Asmaa Hashem, 2021) For sentence-level characteristics, this work provides a hybrid ontology-XLNet sentiment analysis classification technique. The primary goal of the suggested approach allows for the discovery of user social data while taking the derived detailed inferences about sentiment into account according to context. Therefore, in this paper, we examine how using a lexicalized ontology can enhance the performance of aspect-based sentiment analysis by identifying indirect relationships in user social data. In order to create a more thorough context and improve feature extraction, the neighbouring contextual meaning of each embedding word is extracted using the XLNet model and combined with it. Bidirectional Long Short-Term Memory (Bi-LSTM) networks are employed in the suggested method to categorise the elements found in online user evaluations. On six drug-related social data real-world datasets, various experiments focusing on adverse drug reactions (ADRs) discovery are carried out in order to assess the effectiveness of the suggested approach using a number of metrics.

(Julie Polisena , 2021) In this paper 12 studies regarding the use of SA, including ML-based and Lexicon techniques, to gauge public sentiment on social media for certain health innovations were found. Three research looked at HPV vaccinations, two at medical devices, three at pharmacological therapies, and two at HPV vaccinations. The results of these applications should be regarded as exploratory due to the constraints and intrinsic variances among SA techniques. The value of SA is based on the volume of data that can be quickly gathered and analysed to map the context and challenges related to a particular topic to initially inform later stages of systematic analysis that may advise decisions about treatments and technologies.

(Wisam Subhi Al-Dayyeni , 2021) In this paper a thorough analysis of e-nose that highlights the contributions made by researchers in the field, summarises their findings, and identifies problems for upcoming researchers. Methods: For a period of seven years (from 2013 to 2020), three search engines—IEEE Explore's online library, Web of Science, and Science Direct— were used in a systematic manner to find papers that were being used in the e-nose area. The criteria of the research for greater comprehension in the realm of e-nose took into account both technological studies and reviews of the medical literature. The publications were divided into four classes and categorised in accordance with the research's goal. Following the screening of research papers using the exclusion and inclusion criteria, 54 articles were chosen as the final set. Results: The taxonomy used in this study was divided into four groups. The first one (9/54 publications) introduced the use of the e-nose for categorization purposes and gave proposed ways for doing so.

(Yue Han , 2020) This study proposes a precise sentiment analysis task that seeks to determine the polarity of a given target in a sentence. The research of fine-grained sentiment analysis based on drug reviews is built on the aspect-level sentiment analysis dataset SentiDrugs. has the highest rate of acceptance They made forecasts with less correlation. a reduction in characteristics to boost prediction accuracy. A lengthy training period and falling into the local optimum. Systems that under- or over-perform large payloads are caused by inaccurate models.

(Celso Luiz, 2020) This study presents an approach created by a multidisciplinary team made up of reliability engineers, ergonomists, psychiatrists, and information technologists to quantitatively take into account the effect of psychotropic drugs on the evaluation of the human reliability of Operation and Maintenance (O&M) staff at a hydroelectric plant. The first stage in achieving the desired goal was to identify medicines that have a side effect that affects psychic-cognitive/sensory/motor functions and the frequency (probability of occurrence) of the effect. Public and private drug databases were mined for this. The effect of each medicine on the impacted functions was measured using a qualitative (symbolic) scale that was afterwards converted into numerical values.

(Mihaela Ghita , 2020) According to this work, Due to the rapid advancements in automation, robotics, artificial intelligence, sensors, etc., any sector of medicine is predicted to undergo a paradigm shift with the implementation of the integrated healthcare paradigm, which is based on Health 4.0. The two goals of this article, which are addressed to various audiences, are to: i) increase anesthesiologists' awareness of the value of incorporating automation and data exchange into clinical practise in order to give alarming situations more attention; and ii) present actualized insights from drug-delivery research in order to open a window towards precision medicine with noticeably better human outcomes.By using control techniques, depth of anaesthesia monitors, patient modelling, safety systems, and validation in clinical trials, this article provides a succinct review of the recent evolution of closed-loop anaesthesia administration control systems. Anaesthesia control has undergone radical modifications for decades, evolving from straightforward controllers to integrative systems including two or more components, but has not yet made the breakthrough of an integrated system

III. PROPOSED SYSTEM

The feasibility of using sentiment analysis to drug reviews is investigated in this proposed system, and the performance of readily accessible sentiment lexicons in the medical field is assessed. For reliable and efficient sentiment analysis of the drug reviews, a hybrid technique is suggested. To attain high accuracy, learning-based and lexicon-based approaches of sentiment analysis are combined for this aim. One of the crucial steps in converting the chaotic data into a structural format is the pre-processing of the input data. It seeks to enhance the quality of the input data so that models can extract unique features and comprehend patterns better. The drug reviews use a mix of capital and lower-case letters, stop words, and punctuation, which impacts the model's ability to learn.

Since probabilistic deep learning models are case-sensitive, they will treat the words Effect and effect as two separate words when they occur. Therefore, the text of drug reviews is changed to lowercase in the first stage of pre-processing. Split Validation is used to evaluate a learning operator's performance, and the data set is divided into training and test portions. The subsets can be constructed via the Split Validation operator using a variety of sampling techniques.

The suggested model is constructed using cross validation, which prevents sampling bias. The primary goal of the attention layer is to comprehend drug review words in relation to the target and extract the crucial sentiment data for determining sentiment polarity.

Utilising the pretrained weights from the brief text-level classification task, the LSTM layer and SoftMax layer weights are initialized. To assess the effectiveness of the suggested strategy on the publicly accessible UCI dataset, numerous tests are run.

Additionally, the performance of the suggested approach is evaluated against cutting-edge approaches to confirm its effectiveness.

A. Text Preprocessing

We select to perform a simple data cleaning of the texts by changing the texts to lowercase and removing the digits and the frequently present irrelevant words that include a, an, the, them, etc. as well as the punctuation characters present in the data set if the dataset contains numerous common phrases present in every review but have no significant meaning, such as determinants, pronouns from the reviews. In order to create a clean data set with non-redundant and more significant features for analysis, we also intend to delete the non-alpha characters from the data set.

B. Text to Numeric Data Representation

We have employed certain pre-training techniques like BERT in order to encode the reviews into numerical data. We used algorithms such as this because they encode relevance and existence of words in various ways, which is what we intended to do when encoding the importance of the presence of particular phrases. The matrix of numerical values for each word t within each review text was produced using BERT embedding. In our approach, pre-training and fine-tuning are the two processes. The model is pre-trained using a variety of pre-training tasks and unlabeled data. The pre-trained parameters are used to initialise the BERT model, and labelled data collected from subsequent tasks is used to fine-tune each parameter. Each downstream undertaking has its own fine- tuned models, despite being started with the identical pre- trained parameters, refined models.

C. Drug Sentiment Prediction

Preprocessing is carried out since the data set includes ratings from users and multiclass reviews in the feedback area. Tokenization, lower case conversion, lemmatization, refinement by deleting stop words, and sentiment word collecting are all steps in the preprocessing process. Our model's positional encoding and autonomous attention system make up its context-aware portion. To learn text representation while taking the absolute position of words into account, we supplement the word embedding with positional encoding vectors. We choose to assess sentences that include one among the things we collected in the previous stage, and we put those sentences through a BERT classifier to get votes depending on the likelihoods that the entity has a feature aspect, a feature, or a feature aspect. a feature of a product or not. The votes for each of the entities are added together, and we get a list of selected attributes as a result.

IV. ARCHITECTURE DIAGRAM

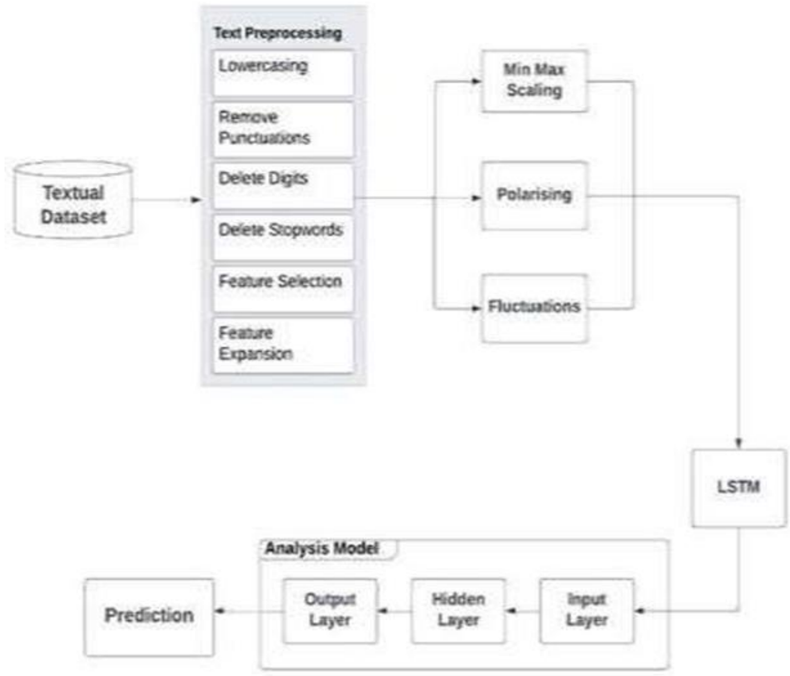

Fig 1. System Architecture Diagram

This Architecture Diagram shows the process of Drug Recommendation System Using UCI dataset.

A. Textual Dataset

The UCI drugs.com dataset is a widely used dataset in the field of natural language processing and healthcare. It consists of over 215,000 reviews written by patients on various drugs for different medical conditions. The reviews were collected from the Drugs.com website and cover a diverse range of therapeutic areas, including diabetes, depression, hypertension, and more. Each review in the dataset contains the drug name, condition

being treated, review text, rating, and demographic information such as age and gender. The dataset is labeled, with each review rated on a scale from 1 to 10, making it useful for sentiment analysis and opinion mining.
Researchers and practitioners use this dataset for various purposes, such as drug recommendation systems, identifying adverse drug reactions, and analyzing the effectiveness of drugs based on patient feedback. The dataset can be used to train machine learning models to predict the effectiveness of a particular drug for a particular condition based on patient reviews.

B. Text Preprocessing

Drug recommendation systems are designed to provide personalized drug recommendations to patients based on their medical conditions, symptoms, and other relevant factors. Preprocessing of data is an essential step in the development of these systems, as it helps to ensure the accuracy and effectiveness of the recommendations.
The first step in preprocessing which involves removing any irrelevant or redundant information, such as duplicates and incomplete records, and standardizing the format of the data.
Next, feature extraction is performed to extract relevant information from the data. This involves identifying and selecting the most important features or attributes of the data, such as drug name, dosage, and patient demographics, that can influence the drug recommendation.
Finally, the preprocessed data is split into training and testing sets for model development and evaluation. The training set is used to train the recommendation model, while the testing set is used to evaluate the performance of the model and validate its effectiveness in providing accurate and personalized drug recommendations.

C. Min-max scaling, polarizing, and fluctuation

Min-max scaling, polarizing, and fluctuation are techniques that are typically used in data analysis or machine learning tasks. These techniques are applied to transform and prepare the data for further analysis or model training.
Min-max scaling is a normalization technique that rescales the range of data values to fit within a specified range, usually between 0 and 1. This technique is applied before feature extraction or dimensionality reduction to standardize the feature values and ensure that each feature has equal importance during model training.
Polarizing is a technique used to transform data by assigning polarities to indicate the direction of change. This technique is typically applied after sentiment analysis or feature extraction to identify the sentiment of the data and assign polarities accordingly.
Fluctuation is a technique used to identify and remove noisy data points or outliers from a dataset. This technique is usually applied after feature extraction or dimensionality reduction to remove the noise and improve the quality of the data.

D. Analysis Model

The input layer, hidden layer, and output layer play crucial roles in processing and generating drug recommendations in a Drug Recommendation System that utilizes LSTM architecture. The input layer processes sequential patient data, while the hidden layer retains and processes relevant information. The output layer produces the final prediction of the recommended drug, which is mapped through a SoftMax or dense layer. Overall, the analysis model of the Drug Recommendation System using LSTM is a powerful tool for suggesting drugs to patients based on their medical history and symptoms.

E. Prediction

The prediction phase of a Drug Recommendation System that uses LSTM architecture involves the input layer receiving patient data, the hidden layer selectively processing relevant information, and the output layer producing the final prediction of the recommended drug, which is then mapped through a softmax or dense layer. The accuracy and reliability of the predicted drug recommendation depend on the quality and completeness of the patient data and the effectiveness of the LSTM model.

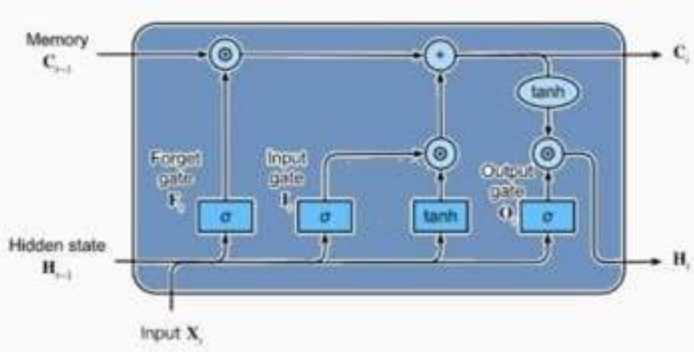

Fig 2. LSTM Architecture Diagram

LSTM (Long Short-Term Memory) is a type of Recurrent Neural Network (RNN) architecture that is designed to effectively model and process sequential data. The main advantage of LSTM over traditional RNNs is that it is able to capture long-term dependencies in the sequence data.

LSTM architecture consists of three main components: the input gate, the forget gate, and the output gate. Each gate is responsible for selectively filtering and processing information in the sequence data.

The input gate controls how much of the new input information should be added to the memory cell. The forget gate controls how much of the old memory information should be retained or forgotten. The output gate controls how much of the memory information should be used to produce the output of the LSTM.

The memory cell is another important component of the LSTM architecture. It is responsible for storing and retrieving information over longer periods of time. The memory cell is updated based on the input gate and the forget gate, which determine how much new information should be added and how much old information should be retained.

The LSTM architecture also includes a set of activation functions, such as the sigmoid and tanh functions, that are used to control the flow of information and produce the final output. These functions allow the LSTM to selectively filter and process information in the sequence data.

Overall, the LSTM architecture is designed to effectively capture and process long-term dependencies in sequential data. The input gate, forget gate, output gate, and memory cell work together to selectively filter and process information in the sequence data, allowing the LSTM to effectively model and generate predictions for a wide range of sequential data applications, including language translation, speech recognition, and time series prediction.

V. RESULTS AND OBSERVATIONS

By giving medical practitioners a useful tool that helps in their decision-making when prescription pharmaceuticals to their patients, the recommendation system has the potential to revolutionise the healthcare sector.

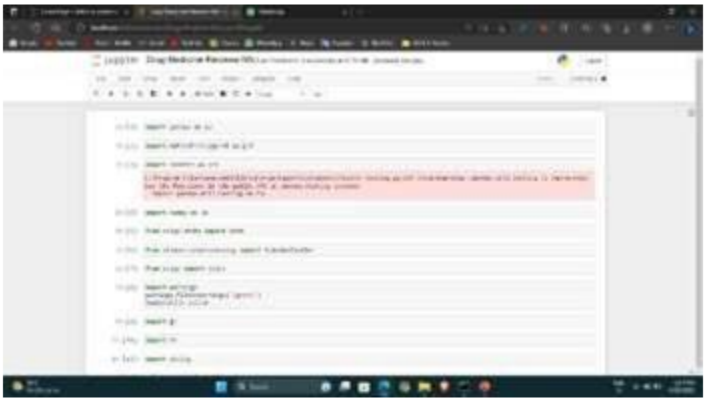

Fig. 3 Import libraries

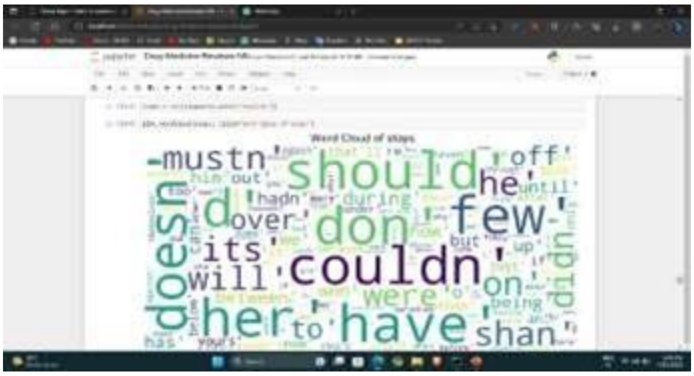

Fig.4 Word cloud

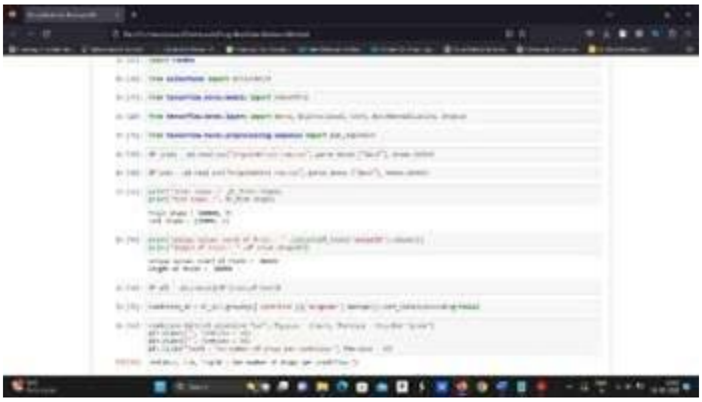

Fig.5 UCI dataset

VI. CONCLUSION

By displaying the most helpful review, it can significantly reduce the amount of time a potential audience will have to spend on it. In this research, we offer a context-aware encoding based method for comprehending the underlying structure of the review by learning dependencies between terms. With the aid of comprehensive trials on the UCI medicines review dataset, we demonstrate that the performance is unmistakably better than that of alternative neural models. In order to analyse users' sentiments, this work addresses the issues of the need for manual annotation in a learning-based approach and the domain specificity of sentiment lexicons. To do this, it combines approaches for labelling and classification that are lexicon-based and learning-based. Additionally, tests on datasets from other domains demonstrate the efficiency of the suggested approach.

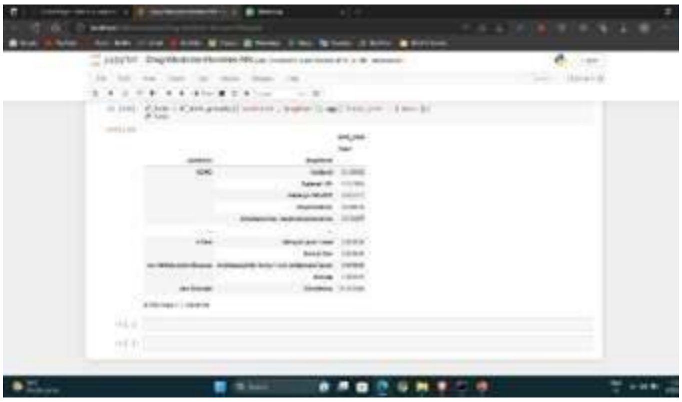

Fig.6 Helpfulness Prediction

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