Sentimental Analysis on the pharmaceutical drug reviews with Deep Learning and comparative study with ML algorithms

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Data Analytics

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Sentimental Analysis on the pharmaceutical drug reviews with Deep Learning and comparative study with ML algorithms

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Abstract

For any health issues, we usually have more than one proven system for treating the illness. This applies to the drugs that could be used for treatment. It's very obvious that we need to have a comparison mechanism to evaluate which drugs are the best from what is available in the market for usage. Sentiment analysis is one of the widely used techniques for collecting opinions from a large group of people using social media, blogs and different other sources as well. The traditional approach is using machine learning techniques to process the data and create a model that performs the sentiment classification. This research presents a comparative study of the traditional ML approach with the deep learning techniques in which we going to apply the concept of sentiment analysis for understanding the opinion in the medical drugs. In the research, we have compared the algorithms in the traditional machine learning techniques like Naive Bayes, generalized linear model (GLM), Logistic Regression (LR), Fast Large Margin with the deep learning approaches like Artificial Neural Network(ANN) and Recurrent Neural Network(RNN) algorithms. We have materialized the code for the RNN algorithm which is Long short-term memory(LSTM) and the rest of the models are compared based on the results generated from the RapidMiner tool. For the vectorization, we have applied the concept of term frequency-inverse document frequency (TF-IDF). Finally, a system was built to classify the sentiment using the Flask Python framework.

1. Introduction

At a high level, the research is intended to fulfil the gap between the manufactures and consumers in the drug development lifecycle. The aim of the research is to focus on developing a solution with an enhanced approach that would perform sentiment analysis with improved accuracy and performance in terms of model results. To highlight, the concept of sentiment analysis is not new. With this research, we will show the novelty by applying it in the Medical field and comparing the results of different AI techniques.

1.1 Business Problem

Pharmaceutical companies follow a similar pattern for the development of drugs. One of the main parameters in evaluating the medicines is side effects and effectiveness for the illness on the patients. Adverse Drug Reactions (ADRs) is the medical term that is used to denote the side effects caused by the medical drugs. For the pharmaceutical organization, it is essential to evaluate the side effects of the medicine when it is used over a period of time or by people from different regions. The continuous evaluation would save the people living from threatening conditions. To analyse the results of the drugs from a wide range of people, we need to figure out the best mechanism. Once that such mechanism is building the sentiment analysis tool that understands the medical terms and polarizes the review text of the patients from different locations like social media, blogs, etc.

1.2 Background

About the background of the business need, when a drug is getting developed, usually it has to be tested by a wide range of people in the world considering the different factors like weather, food habits, ethnicity and so on. The results should be compromised to get the approval for the drug by the concerned department. Let's take an example of COVID vaccination, a unique process has been followed by the pharmaceutical companies before the vaccine is available for public usage. If you take a look at this journal [1], it is stated J&J COVID-19 Vaccine is paused temporarily as it causes neurological risks and we are hearing about many incidents that are causing side effects on the vaccines that were already tested and released into the market. The pharmaceutical companies don’t have a known mechanism in which patients provides direct feedback. In this scenario, the sentiment analysis comes into the picture in which it could be able to take the data from disparate sources like social media text, blogs, and so on. And analysing the review text with the model should help us to extract how positive or negative the patients feel about using a particular drug. The extracted information could help the pharmaceutical companies to address the problem that the patients are facing. Some of the drugs could create an impact when it is used for a period of time, and to be realistic, such feedbacks could be collected only by analysing the public comments from social media and other sources.

1.3 Medical Drug Adverse Effects

As per the research[3], adverse drug reactions (ADRs) is one of the main reason for causing morbidity and mortality which is caused by the drugs that are being used for treatment and it's a leading one. The reports provided by ADR is important for ensuring the safeness of drug. In the research, it is also highlighted that still, we have pieces of evidence that there are knowledge gaps between the pharmaceutical companies and the medical drug users. As per the report, it is stated that 3.5% of hospital admission is happening due to ADR's. The research also discusses the measures that we are taking up to fill the gap between the patients and pharmaceutical companies by defining an appropriate process to overcome the barriers.

On another research[5], it is stated that serious adverse reactions were faced by the people who got vaccinated with the papillomavirus (HPV) vaccine. The symptoms of the side effect have developed over a period of time. It is stated that the issue is with the process in which we develop the drug, promote and distribute it, but we have gaps in monitoring the adverse events of the drug. It is stated that the pharmaceutical companies are responsible to ensure the safety of a vaccine by taking the required actions which include monitoring the side effects of the drug so that the impact could be reduced.

1.4 Research Questions

The research hypothesis is the statement of expectation, which will be tested by the research. The hypothesis that we have set for our research are, the recurrent neural network (RNN) architecture outperforms traditional approaches like machine learning for performing the sentiment analysis in the drug reviews, we have techniques to understand the human language with the parsing functionality and the people’s discussion on social media/blogs could be used to extract opinions of any products or service.

- In what way performing the sentiment analysis using the deep learning technology could be beneficial in obtaining the results when compared to machine learning technique?
- What are the procedures that need to be applied in programming to understand the context of the human language and understand the opinion in the text as well?

1.5 Scope

The scope of the research work is to develop a sentiment analysis tool that performs the classification of the review text to positive or negative based on the knowledge dataset that we have provided to the model which is built on a specialized ANN LSTM deep learning algorithm. And also compare the deep learning approach with the traditional machine learning approach to witness the improvement in the performance of the new model. On top of that, compare the model with the pre-trained model like Vader. In terms of deployment, the work would be presented from the local machine, as deploying the model in the cloud servers like Amazon, Azure would require additional knowledge and time and we are not aware of the cloud systems.

2 Related Work

With the help of the background study, we analyse the importance of developing the research work on the chosen business problem which is applying the sentiment analysis on the drug reviews. On top of that, we should be able to figure the algorithms that could be applied for the implementation.

2.1 Review On Sentiment Analysis

In the research [8], Applying the Natural Language Processing steps for the text datasets is detailed and the concept was applied to process the financial documents. The importance of having the model trained with the domain-specific vocabulary, styles and meanings is highlighted in the research. Different languages like English, French and Arabic was used in the model training and word embedding was done for the languages that were shortlisted. In order to evaluate the effectiveness of the embeddings, we started by evaluating the English embeddings on a sentiment analysis classification task using the existing Financial Phrase dataset and show improved performance over a standard GloVe based model using convolutional neural networks. From this research, we have identified the concept of applying natural language processing in processing human text. On top of that, the approach of handling the multiple languages could be referred to, for the implementation.

As per the author of the research [10], the usage of web tools has tremendously increased and generated a huge volume of data over the platforms like social media, blogs, etc. With the available data, we could extract the relevant information required for running a business or even making important decisions by the government. In relation to applying such techniques, sentiment analysis holds major importance as it comprises the techniques for understanding the human language and the result of the opinion of the user in any context. The deep learning approach is proposed in the research work and helped us to understand the list of tasks that are involved in preparing a model for performing the sentiment analysis task. The research also highlighted the related areas like using the pre-trained model like bidirectional encoder representations from Transformers (BERT) for applying the natural language processing.

As per the author [4], the accuracy of the sentiment analysis model could be improved by applying the Improved Word Vectors (IWV). In the research, lexicons were used with the word vector to improve the capability of finding the sentiment of the text. It is also stated that Word2Vec pre-trained model uses the concept of Improved Word Vectors and with that implementation, the performance of the model is improved by 2%. It is vital to enhance the natural language processing (NLP) and text classifications techniques due to its fast growth, the author says. In this research, the method of Part-of-Speech (POS) tagging is highlighted, which could help the application to perform the sentiment with keeping the whole context in consideration.

2.2 Conclusion From Literature Review

From the background study, we have understood that we need to compare the different algorithms for the implementation as we could be able to choose the best one only when we compare the techniques. We have extracted the pros and cons of the research study that already took place in the area of sentiment analysis. Understanding the existing process is essential, as we need to anticipate the scenarios that might lead to the decrease in the performance or accuracy of the sentiment analysis model that we develop.

3 Methodology

The research methodology aims at describing how the research will be conducted starting from the data analysis phase to the implementation techniques that will be followed over the research process. In terms of process, we have followed CRISP-DM methodology which has phases clearly defined for the implementation of the research work.

3.1 Dataset For Modelling

The dataset contains the text and ratings that the patients have entered about the illness and the reviews for the drug that they have consumed. The dataset has much information and anyways, for our research, we are using only the reviews and rating column which should be sufficient to extract the opinion and train the model with the extracted information. The dataset is already pre-processed and have a separate set for testing and training. The ratio of the split the 75% for training and 25% for testing.

Link – https://archive.ics.uci.edu/ml/datasets/Drug+Review+Dataset+%28Drugs.com%29

The dataset columns are explained below.

- **Drug name**- Drug Name.
- **Condition**- Condition in medical terms.
- **Review**- Review provided by the patient on the medicine consumed.
- **Rating**- Rating provided by the patient on the medicine consumed.
- **Date**- Date in which review is casted
- **Useful count**- A count on people found the review as a useful one.

3.2 Data Analysis

For training the machine learning or deep learning model, we need to have a dataset that defines which one is a positive medical review and which one is not. We are following the supervised learning technique in artificial intelligence, so it is required to train the model with the knowledge to identify the polarities. EDA is mainly performed to extract the characteristics of the dataset that will be provided to the model for the training purpose. We apply different visualization charts to view the characteristics as it would be easy to understand when compared to the approach of analyzing the quality of the dataset as it is with the text format.

We have done the below analysis on the dataset and figured out how well the chosen dataset would suit for analyzing the reviews of any specific drugs.

- **Rating Count and Mean Against Each Drug**: From this, we could get to know the drugs that could be excluded for model training as it is completely positive/ negative.
- **Top 10 Reviewed Drugs:** Used to identify which drugs were mostly discussed.
- **Health Conditions in Dataset Reviews:** The reviews related to "Birth Control" was high. Filtered the top 10 records.

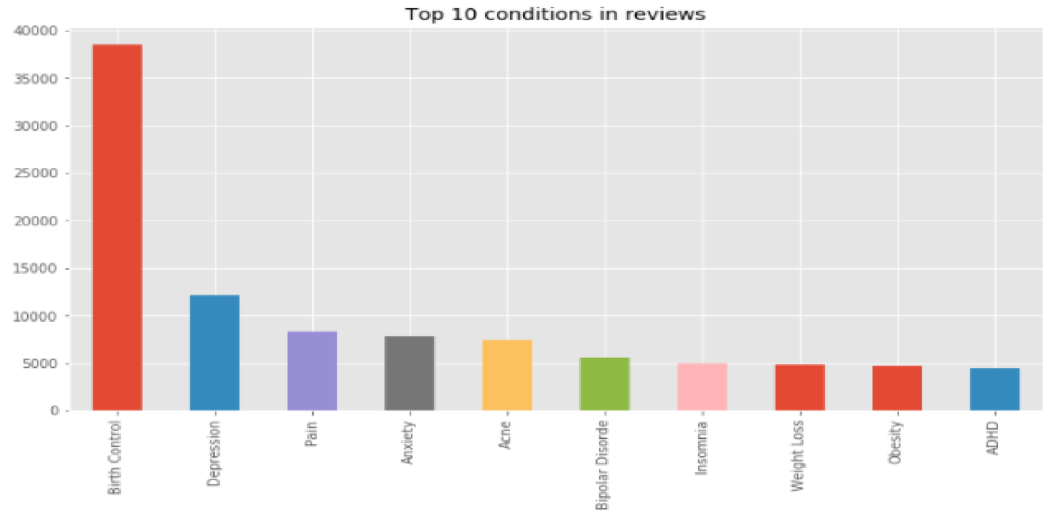

Figure 1: EDA - Top 10 Conditions in Review

- **Top 10 Best Ratings for the Medical Drugs**.
- **Top 10 Worst Ratings for the Medical Drugs.**

From the EDA, we applied to filter on the dataset size to use the drug review text that has sufficient size in length which is set to 200 characters. We have also filtered the dataset with the high number of reviews cast on the treatment, as we couldn't able to process the huge volume of data with the limited system configuration.

3.3 Pre-Processing And Natural Language Processing

The human language which is in the text format needs to be pre-processed before we send it for the model to get it trained for understanding the pattern in the dataset. The steps in the data pre-processing could vary based on the business needs. For example, some businesses might require to consider only the top 100 frequently used words for classifying the text. On the other hand, some other business requires to consider only the top 50 frequently used words for processing.

The Natural Language Processing (NLP) task is implemented in research for processing the human language text which is the review text about the medicine.

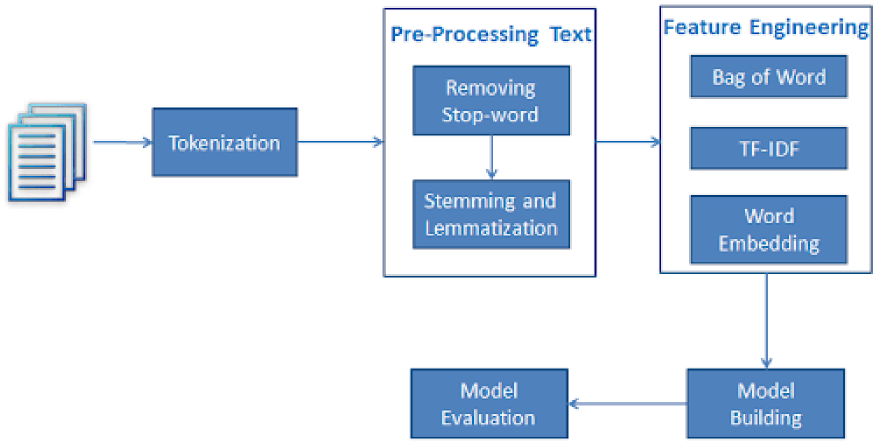

Figure 2: NLP Pre-Processing Steps

To consolidate, at a high level we perform the below operations in NLP.

- The text would be converted into lower case, to avoid the differentiation between the upper and lower case.
- Remove the punctuation; the string package has the definition for punctuation.
- Removing the stop words which is not essential for sentiment.
- Perform stemming, to have a common word.
- Apply tokenization on the pre-processed text.
- Sequencing, which is used to convert sentences into sequences of numbers.
- Padding, to have a common sequence array for neural network processing.

3.4 Deep Learning Approach

From the background study, we have decided to implement the model with the deep learning technique with the preprocessed data. The RNN (Recurrent Neural Network) is an enhanced technique in which we could avoid the limitations that we were facing in the feed-forward neural network. The limitation was exactly on performing the sentiment analysis and the NLP process as the process needs to be put in a way like the input needs to be processed in a sequential manner and utilized by the memory or state in the model.

We have chosen a general-purpose RNN (Recurrent Neural Network) which has different layers like input, middle and output layer for processing. It works in a way, the layers are interdependent with the connections established between the layers. The RNN algorithm is structured like a human being brain which is interconnected with the nodes. The human brain has neurons that interact with each other for decision making. By following a similar approach, the RNN algorithm works with the help of neurons which is layers in terms of algorithm. We have to know that algorithms don't fit perfect for all the solutions. For example, as per the records, Artificial Neural Networks performs well in solving classification and regression problems. This is also decided based on the data type of the dataset that we choose for model training.

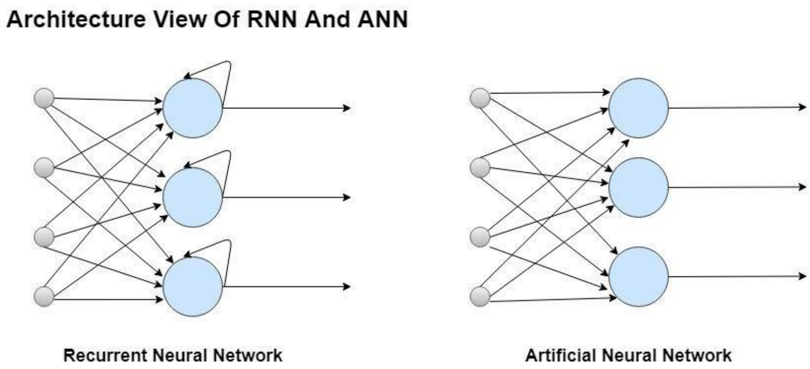

Figure 3: Structural difference between RNN and ANN

We have different types of data types of the dataset and some of them are textual dataset, audio, video and so on. As per the records, the Recurrent Neural Network (RNN) algorithm works well in the textual dataset when compared to ANN as we need to establish a sequential process and also the features in the dataset has high dependencies. RNN is a type of ANN with a neuron based design in the architecture. For our research implementation, we have chosen the Long short-term Memory (LSTM) algorithm which is classified under the Recurrent Neural Network.

For our research implementation, we have chosen the RNN algorithm that is capable of remembering the overall context of the statement, instead of just analyzing the words individually. The LSTM has gates that support the concept of holding the information over a period of time to understand the whole context. For the implementation, the LSTM gates are used, which are the input gate, output and the forget gate. The gates have a different purpose for processing the information. For example, the forget gate is designed to analyze which information needs to be held on to processing and which one needs to be discarded for processing. So with this approach, the model could hold the essential information and discard the remaining from the processing steps. With the gates, the LSTM memory is designed to hold the previously processed information and take the decision accordingly. This helps to achieve the implementation contextual model, instead of the limit one that is process-based on individual tokens.

The LSTM model accepts the vectorized numerical input which is in the form multi-dimension array. The model has a memory unit to store the data it is processing and organize the data accordingly. The segregated training dataset is passed to the model for getting it trained over multiple iterations to understand the pattern in the dataset. The model provides the result in 2 different formats, one is a range value which would be in the range of 0 to 1, the value less than 0.5 is considered as a negative review and above 0.5 is a positive review, per se. The second one is Boolean data, in which 1 represents a positive review and 0 represents the negative. The polarity classes are defined when we prepare the dataset for model training in which we have considered any rating above 5 is a positive review and the remaining set is a negative review.

For easier model training and for the performance of the model, we have used Rectified Linear Unit (ReLU) activation function. For reusing the developed model, the trained LSTM model weight is stored in a physical location for future use. This approach would help us to get the model trained once and deploy the trained once for prediction across the machines without retraining it again. Over the training process, it is essential to identify a point in which the model has less value on the training loss and more accuracy.

3.5 Machine Learning Approach

The below-mentioned machine learning algorithms were considered for analysis, as all of these models are applied in solving the classification problem. Only the ratings and review text fields are provided for the model as an input, as it would be sufficient to prepare the model for performing the sentiment analysis. We are not intended to have a polarity predict functionality for the shortlisted machine learning techniques. Our aim is to compare the evaluation results and not to have the code implementation.

List of Algorithms:

1. GLM - Generalized Linear Model
2. NB - Naïve Bayes
3. LR - Logistic Regression
4. FLM - Fast Large Margin
5. SVM - Support Vector Machine
6. DT - Decision Tree
7. RF - Random Forest
8. GBT - Gradient Boosted Trees

Naïve Bayes

The Naïve Bayes algorithm is a machine learning technique that could be applied for text-related problems like sentiment analysis. It internally uses the Bayes probability theorem for the classification.

Generalized Linear Model

The Generalized Linear Model is an enhanced version of the linear algorithm. In performing the sentiment analysis using the GLM model, we have the linear combination applied on the independent variables of the dataset and make use of the dependent variable for the probability distribution.

Logistic Regression

Logistic regression works in a different way in which we group the independent variables for calculating the probability and also this model helps to analyze the relationship between the variables which are dependent and independent.

Fast Large Margin

The fast large margin works on the base of the linear support vector. In this approach, we maximize the margin close to the hyperplane and perform the separation. This technique could be the best one in some of the cases and would fit for performing the sentiment analysis as well.

Decision Tree

The Tree based learning algorithms comes under the supervised machine learning methodology. This could be applied in solving the categorical and regression type problems. In the algorithm, the polarity would be calculated on the base of the significant splitter that is extracted on the base of the input variable in the dataset.

Random Forest

In Random Forest Algorithm, we complex the design of the Decision tree with multiple layers and it handles the different samples of data with different variables and processes the data to extract the final decision from each model. The final result would be consolidated with the random forest.

Support Vector Machine

In the Support vector machine, we follow the supervised learning approach, in which we perform the non-linear classification based on the labelled data.

3.6 Evaluation Metrics

The models are evaluated in different aspects like accuracy, recall and classification for comparison with the results of the other algorithms. For our research, we will be developing the model in deep learning and for the machine learning models, we have used the Rapid Miner process for calculating the evaluation metrics and evaluating the results of all the algorithms. The performance of the model results in the RapidMiner process is evaluated on the scale of Accuracy, Classification Error, AUC, Precision, Recall, F measure, Sensitivity and Specificity. Other than that, the Confusion Matrix is used to evaluate the performance. We have chosen to evaluate the model with Accuracy which is one of the basic metrics and it defines the fraction of predictions our model is correct. We have also calculated the classification report which defined the proportion of the misclassified results on the data input. In the LSTM code implementation, we have limited to evaluation of the model on basis of accuracy and classification error. For the purpose of evaluation, we pass the test data to the model for prediction and the results are compared with the expected output.

4 Implementation

At a high level, the implementation contains three steps. At first, we perform the preprocessing of the dataset, then we apply natural language processing toolkit functionality to parse the textual data into the vectors which could be applied by the machine learning and deep learning programs. In terms of coding, python programming provides a package called the NLTK package and this has functions to perform the tasks that pre-process the human language. We have a wide range of community support for this package and it is widely used in the area of NLP. It is an open-source package with having the support on many operating systems for both application development and in the deployed environment.

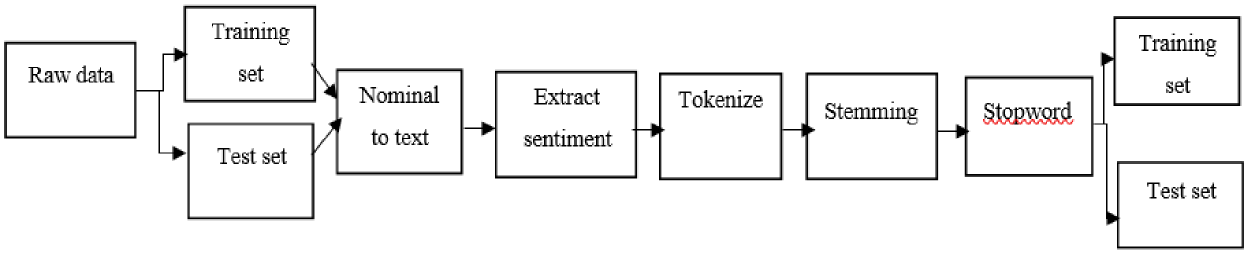

Figure 4: Natural Language Processing Steps

For the implementation, first, we start with loading the medicine reviews dataset. We already have the split dataset, which has both the training and test set; we will be loading both datasets. As a part of pre-processing, we could apply filters like removing the reviews which are really short in size, removing the reviews in the language which is not intended for model training. Next, we will proceed with NLP processing, which is converting the text into lower case, removing the punctuations from the text in which the list of punctuations are already defined in string package, creating an index mapping dictionary on the base of the collection of words from the reviews and applying the often occurring words with lower indexes, perform encoding on the words and labels that will be used for model training. Next, we will apply the padding operation, which is padding or truncating all the reviews to a specific length and it is represented as sequence length. The LSTM model needs to have a common length across the reviews for processing. In this process, all the reviews that are shorter than the sequence length would be padded with 0s and the reviews truncate the words that are longer than the sequence length. For our research model, the sequence length was set to 200 and it could be modified if we need to consider more number of words for processing.

To perform the model training, we load the preprocessed data in data loaders by using PyTorch, which is an open-source library for performing the operations like natural language processing. The operations are performed in batches and the batch size is configured as 256 and it could be increased if we train the model in high-end machines. In the LSTM model, the word tokens in the integer format is converted into embedding of a specific size. Next, we initiate the network and start with the training process. The training process in the standard deep learning is almost similar for any implementations and especially when the PyTorch framework is used for model training. We have used Adam optimizer to improve the performance of the deep learning model training process. The main objective of the optimizer is to reduce the impact of losing the information in the process of model training over the epochs. The Adam Optimize is one of the best techniques that are used for improving the training process and that's the reason we have chosen the same even though we have options like regular gradient descent and stochastic gradient descent. The training are done in a loop and the iteration size is defined as the epoch. The epoch size is defined based on the validation loss; if validation loss is getting decreased, it represents the model is a good fit.

As of the implementation, we need to have a method to provide the sample input and test the developed model with the user inputs. The predict function is written which accepts the user input, the input text will have basic pre-processing steps applied before we pass it for performing the prediction. The result would be binary values, which states whether it is a positive review or a negative review.

For the comparison of the developed LSTM model with the ML techniques, we have applied tool-based techniques to extract the evaluation request. With the limit available, we are not able to compare the algorithms, so we have done the comparison using the data mining tool called Rapid Miner for the model operation and compared the results.

5 Results And Discussion

We have obtained the below results on the comparison of the different models through the research process.

Model	Accuracy	Classification error	Recall	Ranking
RNN lstm	86.0%	15.0%	87.2%	1
Fast Large Margin	85.0%	15.0%	87.2%	2
Generalized Linear Model	84.3%	15.7%	87.2%	3
Logistic Regression	84.1%	15.9%	83.0%	4
Naive Bayes	84.0%	16.0%	87.2%	5
Support Vector Machine	83.3%	16.7%	87.2%	6
Deep Learning	82.9%	17.1%	85.2%	7
Gradient Boosted Trees	82.7%	17.3%	92.6%	8
Random Forest	77.4%	26.6%	92.6%	9
Decision Tree	71.2%	28.8%	97.3%	10

Figure 5 : Model Results

As per our research hypothesis and from what we have extracted from the background research work, we have stated that the deep learning model works best when compared to ML models. To validate the stated hypothesis, we have created the RapidMiner processes with different Machine learning algorithms and compared the evaluations metrics of the model that we have developed in Python programming.

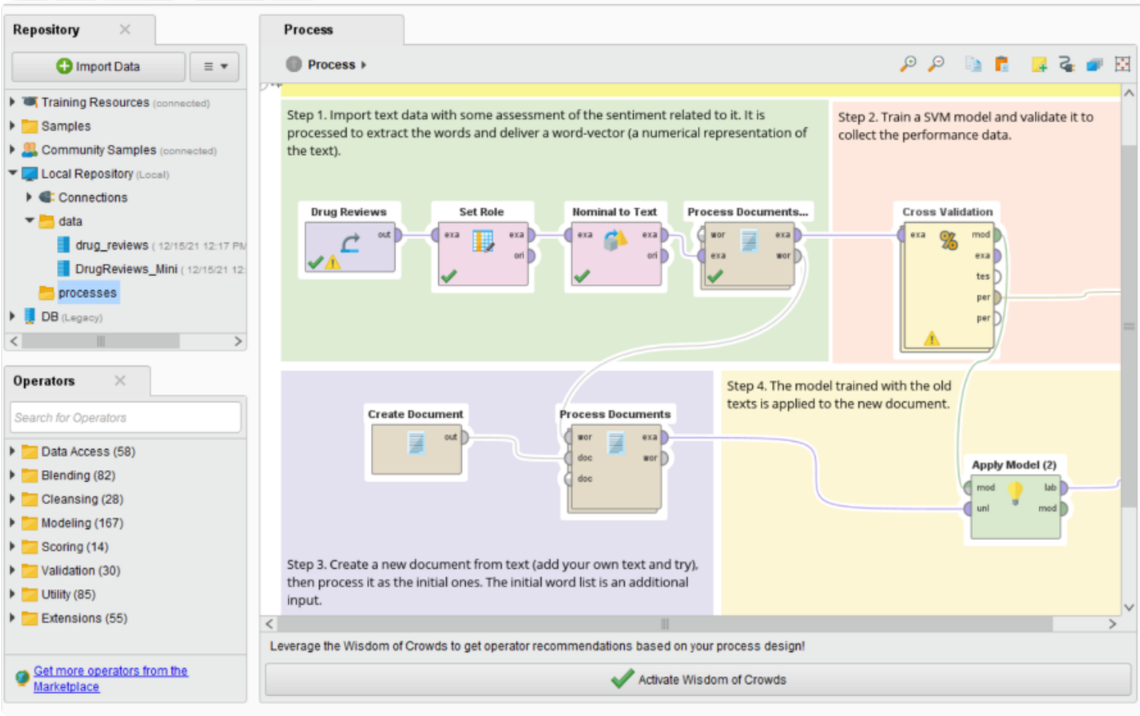

Figure 6: RapidMiner Process For Comparison

The chosen Long short-term memory (LSTM) algorithm which is an artificial recurrent neural network (RNN) architecture for the implementation have given the best results in terms of accuracy and performance. Due to the limited available time, we have compared our deep learning model results with machine learning models like Fast Large Margin, generalized linear model (GLM), Logistic regression (LR), Naive Bayes and few other machine learning models with the help of the data science tool called RapidMiner. So, we conclude, the developed model outperforms the traditional ML models. On top of that, we have compared our specialized model with one of the pre-trained sentiment analysis models, which is Vader Sentiment Analysis for justifying the reason for having a specialized model which understands the medical drug-related terms and context. To conclude, we say that we need specialized sentiment analysis models which understands the domain, even though we have generic ways to calculate the sentiment score for the text.

6 Conclusion And Future Work

From the comparative results, we can conclude that the specialized RNN LSTM has been successfully performed the intended functionality which is performing the sentiment analysis on the text to identify the polarity, which is classified under positive or negative review text. Further, the traditional machine learning models could not outperform when compared to the deep learning techniques. When compared to the traditional machine learning models the Fast Large Margin, Generalized Linear Model, Logistic Regression and Naive Bayes are some of the techniques that suit well for solving the sentiment analysis problem which deals with the textual dataset.

In the future work, the scope of the developed research work could be extended to implement the functionality with different algorithms as well in which sentiment analysis for identifying the opinion could be improved. The results that we have obtained from the current research process would be used as a base for future work in which we will be implementing the intended logic with the different other algorithms and compare the results; instead of just limiting the comparison with the RapidMiner process. On top of that, The research application needs to be moved to the high configured environment like GPU machines to increase the dataset capacity for the model to get trained, which could increase the accuracy of the model as well. On the other hand, we could develop a generic solution that could fit in performing the sentimental analysis irrespective of the domain.

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