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Deep Learning-Based Sentiment Analysis for the Prediction of Alzheimer's Drugs

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Abstract. A growing public health concern, Alzheimer's disease (AD) affects millions of people globally and has a yearly economic impact of billions of dollars. We examine the pipeline of pharmaceuticals and biologics undergoing AD clinical studies. The majority of the time and money spent on clinical trials of potential therapies for Alzheimer's disease (AD) have yielded disappointing results. The Alzheimer's research community is continually looking for new biomarkers and other biological indicators to describe the course of the illness or serve as clinical trial outcome indicators. One upshot of these efforts has been a substantial body of literature presenting sample size estimates and power calculations for future cohort studies and clinical trials with the longitudinal rate of change outcome measures. To be as useful as possible, statistical methodologies, model assumptions, and parameter estimations used in power calculations are frequently not disclosed in sufficient depth. Most dementia cases (60–70%) are caused by Alzheimer's disease (AD). The need for discovering effective medicines to treat AD has increased due to the severity of the condition and the ongoing growth in patient numbers. The medications now used to treat AD can only temporarily reduce the symptoms of dementia; they cannot halt or reverse the course of the illness. Many international pharmaceutical companies have tried numerous times to develop an amyloid-clearing medication based on the amyloid hypothesis but without success. To offer a comprehensive understanding of clinical trials and medication development for AD, we looked at some new impacts to categorize the medication with the help of deep learning techniques for a better and innovative result to reduce the rate of changes of severity. Using a deep learning framework and big data analytics, we developed a strategy called "drug repurposing in Alzheimer's disease" that quantifies the connection between a list of medicine names and the stage of AD as assessed by sentiment analysis.

Keywords. Anti-amyloid, anti-tau, clinical medication trials, neuroinflammation, neuroprotection, Alzheimer's disease.

1 Introduction

Alzheimer's disease is a degenerative condition that worsens with time and damages the neurological system by causing the brain's neurons to die. Higher brain functions eventually diminish due to neuronal death in the brain, which impacts memory and learning along with a decline in motor skills. AD is one of the more common types of dementia, making up around 70% of all dementia types.

These two types are amyloid plaques and tangles [1]. Amyloid plaques are protein deposits known as beta-amyloid that accumulate in the spaces between neurons (twisted protein fibres known as "tau" that build up inside nerve cells). A significant aspect of neurodegeneration is brain

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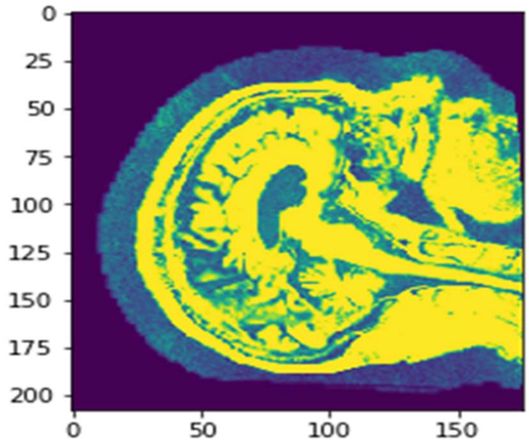

Fig. 1. Representative of Alzheimer's disease (AD) data

shrinkage. Biological signals act as early warning signs for AD before a few minor symptoms first appear as clinical symptoms. Additionally, there are several factors other than aging that contribute to AD, including poor sleep, poor diet, unhealthy lifestyle choices, heredity, and environmental factors.AD is also multifaceted and not just caused by getting older; other causes include sleep difficulties, food, lifestyle choices, genetics, and environmental variables.

AD includes three stages: preclinical, mild cognitive, and dementia. The clinical stage of Alzheimer's disease, which is when symptoms first appear after a protracted period of no symptoms, progresses as the biological procedure develops with the emergence of vital signs. As an increasing healthcare concern, greater life expectancy is the main risk factor for Alzheimer's disease (AD).

An illustration showing how Alzheimer's patients may easily be separated from CN and MCI in MRI brain pictures using the. nii format is plotted in Fig 1. Due to the lack of effective prevention and treatment alternatives, according to projections, the number of people with the disease would more than double over the ensuing decades, from the current 5.7 million Americans living with AD to a projected 13.9 million by 2050 [2]. Long-term care for individuals afflicted is quite expensive in addition to having a direct influence on people's health and well-being.

A total of 200 clinical studies have been conducted to date in the search for AD disorder therapies, however, the majority of these efforts have been unsuccessful, with many of these defeats being due to ineffectiveness or severe toxicity [3]. For a new molecular entity (NME), every unsuccessful clinical trial cost a lot of time and money [4].

Utilizing an existing medicine for a new application, the traditional approach to repurposing involves using the product, maybe in a new dosage or formulation. An approach is to test a therapy hypothesis through repurposing, which might then be enhanced through additional medicinal chemistry and functional testing to become an NME [5].

This could be helpful considering that the fundamental disease processes in AD are still unclear and there is a chance that different disease causes could coexist. Informatics-based strategies for drug repurposing have arisen as drug information databases expand. This could be problematic for a disease like AD, which is poorly understood, characterized by phenotypic and pathological variability, and involves non-proliferating cells.

2 Motivation and Contributions

We set out to build a multipurpose technique that incorporated these datasets since the molecular changes that happen in the brains of persons with changed stages of AD owing to the use of different drugs are statistically reflected in various research.

We focused on expression data through deep learning concerning big data analytics.

A lot of ways to use the diagram of linkage and associated techniques to locate medications that produce comparable transcriptional modifications in a certain medical environment. Previous drug repositioning projects for aging and AD also extensively emphasize data expression.

Despite recent discoveries from drug testing, the disease's frequency has been markedly reduced. These drugs could be able to postpone the onset of dementia. However, a therapeutically useful disease-modifying medication is still a long way off.

To provide more impartial evaluation of CNN performance for patient sentiment analysis, which would provide a solid platform for future research, we first conducted a thorough review of all aspects of Alzheimer's disease.

The remainder of the task has been handled as follows. Section 3 contains an elaborative description of related works. In Section 4, several pertinent existing studies of Alzheimer's disease drug therapy are summarised.

Section 5 presents a detailed description of Alzheimer's disease—clinical stages, Section 6 describes the treatment objective (disease-specific versus non-disease-specific).

In Section 7, the proposed methodology is discussed. Section 8 presents the experiments. In Section 9, we present the results and discussion part. Thereafter, section 10 concludes the study.

3 Related Work

Deep learning, one of the classification performances, has just witnessed a notable surge in its use for sentiment classification. Despite the broad use of sentiment analysis in various industries, the pharmaceutical industry has received much less attention than other application areas. Rules and sentiment lexicons were mostly utilized in early work on sentiment analysis of drug reviews to determine if a review was generally favourable or negative.

A mapping between words and vectors known as word embeddings model can be used to determine word similarity. Word embeddings have since been employed in numerous NLP tasks with great success. One of the first to employ word embeddings in sentiment analysis of patients [6]. The researchers investigated various machine learning methods, including SVM, Naive Bayes, and Random Forest, which were trained using word embeddings, sentiment analysis, lexical, syntactic, semantic, and other aspects to represent texts.

The Adaptive Recursive Neural Network (AdaRNN), is a new model that divides tweets into one of three sentiment categories: positive, neutral, and Negative [7].

According to experimental findings, the AdaRNN had a 66.3% accuracy rate. Researchers' latest RNN model version, the Gated Recurrent Neural Network (GRNN), achieved accuracy rates of 66.6% (based on Yelp 2013-2015 data) and 45.3% (Based on IMDB data) [8]. There were three or more sentiment labels, as was the case in all of these experiments.

The binary classification of sentiment using Long Short-Term Memory (LSTM) achieved 82.1% accuracy on movie review data [9]. When given seven distinct types of input, the CNN model with a single convolutional layer produced a maximum accuracy of 89.6%. [10]. With different datasets researchers presented three-way classification and achieved a maximum accuracy of 94.2% [11]; NB-SVM was their highest-rated model.

Researchers developed a hashtag recommender system using the skip-gram model and convolutional neural networks (CNN) to learn semantic phrase vectors, taking into account the importance of hashtags in sentiment analysis [12]. These vectors employ LSTM RNN to classify hashtags based on features.

Results show that this model outperforms more widely used models like SVM and Standard RNN. This investigation is based on the fact that it was subjected to standard AI approaches like SVM and collaborative filtering; the semantic features are lost, which has a significant impact on obtaining a reasonable expectation.

4 Alzheimer's Disease Drug Therapy

There is still a lack of clarity on stage one of AD, and it can be difficult to identify trends through guided MRI image diagnosis. Manually diagnosing and extracting characteristics takes a lot of practice

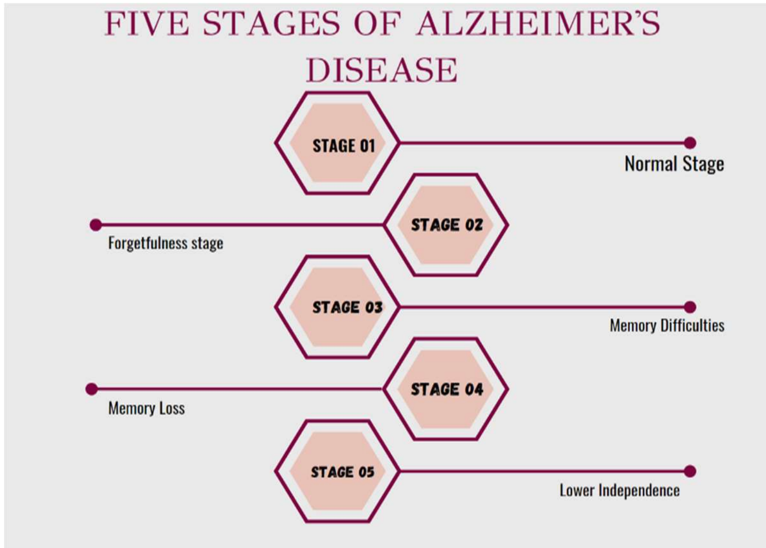

Fig. 2. The stages of Alzheimer's disease

and time. The goal of this project is to create numerous structures for the primary identification of AD employing a variety of approaches for evaluating and interpreting different medications utilizing both deep learning and machine learning techniques as well as a combination of the two.

Additionally, classical algorithms are combined with hybrid features that are taken from CNN models. The U.S. Food and Drug Administration (FDA) has authorized treatments that fall into two categories: those that may prevent or delay the clinical deterioration of Alzheimer's patients, and those that may temporarily lessen some of the symptoms of the illness [13].

It is crucial to consult a healthcare practitioner before deciding on any course of treatment to ascertain whether it is necessary. A doctor with experience using these kinds of drugs should keep an eye on patients taking them and make sure the suggested guidelines are strictly followed.

In this paper, we summarise the available pharmacological therapy for AD and highlight prospective new technology while considering the underlying aetiological mechanisms. The most precise method is the Monte Carlo (MC) dose calculation, but it also takes the longest.

As a result, we made an attempt to study the medication through a chart of the many medications used by medical professionals to treat Alzheimer's at various stages.

5 Alzheimer's Disease - Clinical Stages

In the explanation below, various stage characteristics are categorized. however, we'll use the five key stages listed below in Fig.2 format to help you comprehend.

1. Typical adult. No reduction in functionality.

2. Typical aging adult knowledge of one's functional deterioration.

3. A very early stage of Alzheimer's noticeable deficiencies in difficult work environments.

4. Managing finances, planning events, and other complex duties require assistance for those with mild Alzheimer's.

5. Moderate Alzheimer's requires support in making appropriate clothing selections.

6. Moderately severe Alzheimer's disease needs assistance with dressing, washing, and using the restroom, suffers from faecal and urine incontinence.

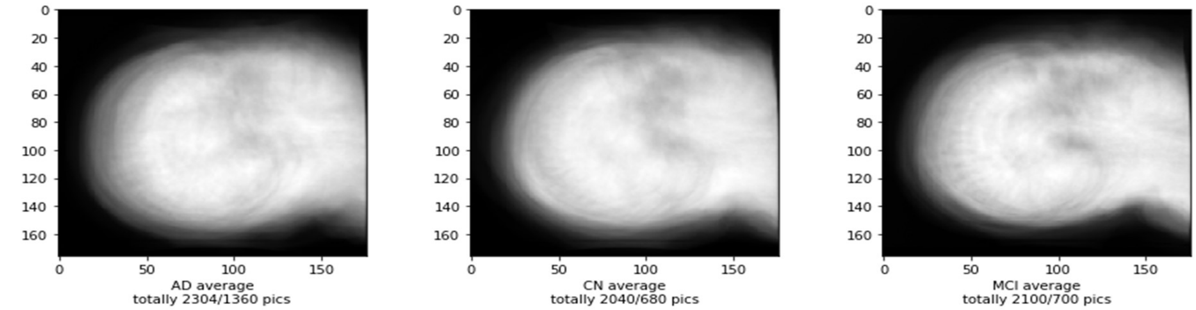

Fig. 3. Brain MRI scans at various phases from the ADNI database

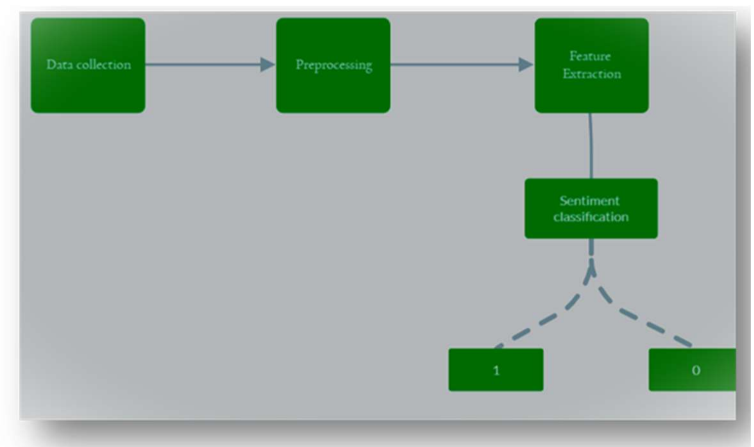

Fig. 4. The proposed workflow architecture

Speech comprehension in those with severe Alzheimer's decreases to around 12 understandable words. loss over time of the ability to walk, sit up, smile, and hold one's head high.

6 Treatment Objective (Disease-Specific Versus Non-Disease-Specific)

From the age-matched, cognitively healthy control cohort in ADNI, it is possible to evaluate the potential impact of age-associated deterioration that is not responsive to treatment. Fig.3. shows various stages of brain MRI images from the ADNI database.

Systematic review: We looked at medications undergoing Alzheimer's disease (AD) clinical trials that were listed in the Drugs.com database maintained by the federal government [14].

Interpretation: For the treatment of AD, medicines are now undergoing clinical studies. Ninety-seven of these medications are disease-modifying substances designed to alter the biology of AD. Twelve of the medications are being developed to treat neuropsychiatric problems, while 12 are purported cognitive enhancers.

There has been an increase in the number of disease-modifying treatment candidates over the past five years, as well as a higher variety of pharmacological targets, more repurposed compounds, and a greater integration of biomarkers into research programs.

The number of medications for various ailments is varied for each condition, as you can see from the image above. It should be noted, however, that the comment "useful" appears in the condition, which appears to be a crawling error. we investigated it to get a better understanding of it. The top medications in the data set that received a rating of 10/10 are displayed in a bar graph with percentages.

7 Methodology

To forecast CN and AD, we used the attributes in deep learning models. The two primary parts of our technique are feature selection and model construction. The number of various types of data, including structured, semi-structured, and unstructured data, is increasing enormously in the big data era.

Since text accounts for the majority of them, studies on structured analysis have been actively done from the past to now. Because texts may contain categorical descriptors like "sentiment," text categorization has drawn a lot of interest (e.g., positive or negative) Sentiment analysis uses positive, neutral, and negative categories, whereas emotional analysis uses mood categories.

Machine-learning methods have been employed in various research for text classification. Despite being extensively used and performing pretty well, machine learning approaches heavily rely on manually-defined features, when much more effort from specialists is needed for such feature description.

Due to their potential to reduce feature-defining effort and provide reasonably high performance, deep learning approaches have gained attention recently. We focus on text data sentiment in this paper and present an architecture of a deep learning model called Convolutional Neural Network (CNN). By experimentally comparing our suggested network to existing machine learning models, we show its efficacy.

The following can be used to summarise the contributions of this paper: (1) To enhance performance for lengthy and complicated texts, we develop an architecture comprising consecutive convolutional layers; (2) We compare the architectural features of our models to those of other models, and (3) Use the Convolutional Neural Network model to categorize two-fold sentiment This assertion has been validated by experiments, and the discussion is illustrated in Fig. 4 below to extract pertinent data that can be utilized to evaluate both the beneficial and detrimental impacts of a medication on a patient's response, step-by-step data processing is employed.

8 Experiments and Results

8.1 Dataset

For the purpose of determining the magnitude and frequency of adverse drug responses associated with various therapies, PubMed, the Cochrane database, PhycINFO, Embase, Medline, and the Drugs.com website were used to search for English and non-English writing.

We specifically employed several collections of patient relatives' reviews from the Drugs.com website, which we collected in accordance with the patient's level of drug satisfaction.

This dataset contains patient assessments of specific drugs as well as details on co-occurring conditions. There are 326,069 reviews of medications in the corpus as a whole. A ratio of 75:25 separates the corpus into a training dataset and a test dataset.

There are 13,185,853 words in this model's lexicon. The majority of the reviews were for the positive class, with the reviews for the negative class appearing last. Overall, the positive class had more words than the negative class. 60,104 unique words make up the total, which is not the least.

Example: memantine (one of the names of Alzheimer's medications). According to one of the patient's carers, the medication review is “my mom has on this medication for one year and her condition is getting worst she’s hallucinating, aggressive, and extremely confused.” Here, the patient's caretaker's evaluation is negative.

The review of a different family member is “it was a wonderful drug for my mother, with dementia, at 77”. Positive comments have been made on the medicine score of the patient's carer. We analyse the database using several subgroup analyses.

In addition to a group of individuals who get the treatment to be assessed, it is a method of assessing a medical therapy. Both the drugs.com and ADNI databases provided the data for our model.

Table 1. Classification comparison analysis of SVM+ Naive Bayes, Decision tree, Random Forest, and CNN

Model	Class	Precision	F1 score	Accuracy
Decision tree	Negative Positive	81 83.2	81 82	84
Random Forest	Negative Positive	79 81	77 79	80
SVM + Naive Bayes	Negative Positive	80 82.3	80 84	87
CNN	Negative Positive	83.2 84	80 86	88.02

Please visit the ADNI website for further information if you would want an image database to classify stages. A public-private partnership called ADNI is established in 2003 to study diseases including Alzheimer's. In this investigation for better research with study resources, researchers gather data that is distinct from that on this website.

With a standardized protocol for AD prevention and therapy, the Alzheimer's Disease Neuroimaging Initiative (ADNI) enhances clinical trials for better results. A greater understanding of diagnosis in the medical industry has been made possible because of ADNI.

Two participants, ADNI1 and ADNI2, obtained 3.0 T T1-weighted pictures. The Neuroimaging Informatics Technology Initiative (Nifti) file format is used to download each image. An Intel Xeon silver 4110, 2.1GHZ-3.5GHz x8 core high-performance computer (HPC) was used for the diagnostic MRI analysis with CNN.

With the Nvidia GTX1080Ti Pascal chipset, we used the GPU platform, which has the greatest number of ALU cores. Cuda(x) is kept in the GPU (Graphics Processing Unit), which also houses a number of external libraries and has a channel that can be created by a company.

8.2 Classification

As was said before, RNN and CNN are the two most common types of deep learning techniques for sentiment categorization [15]. Here, we offer a convolutional neural network model, whose architecture was deliberately planned for efficient sentiment analysis. The benefits of using CNN for text analysis are discussed in the next subsection. Several datasets have employed the commonly known CNN algorithm, removing the important characteristics as the "convolutional" classifier scans the dataset.

The same CNN function might be applied to the text if the incoming information is 1-dimensional. Local text information is saved in the text extent as the filter moves around, and significant features are extracted. CNN is therefore a useful tool for text classification. A 2D matrix is projected onto a small-dimensional vector during the embedding process. The pooling layer's input is the matrix that was processed by the subsequent convolutional layer.

This study applied the max-pooling method, which chooses the highest number to represent the extreme values. We used the max-pooling technique since a feeling is often transmitted by a combination of multiple words rather than in every word of the sentence. The second convolutional layer's output matrix, which is produced by the pooling layer, is slid with any arbitrary stride to produce output vectors.

The output vectors produced by max-pooling are substantially lower because it is the layer that sends the largest value among numerous values to the following layer. In other words, the pooling layer provides a supporting role while the key information is extracted from the context by the convolutional layer.

The output's two-dimensional feature map is flattened after going through the pooling layer to provide it to the fully connected (FC) layer in a one-dimensional format. Only one-dimensional vectors are accepted by the FC layer, so before being used as an input, the 2D vector supplied by the pooling layer must be flattened. All of the input and output

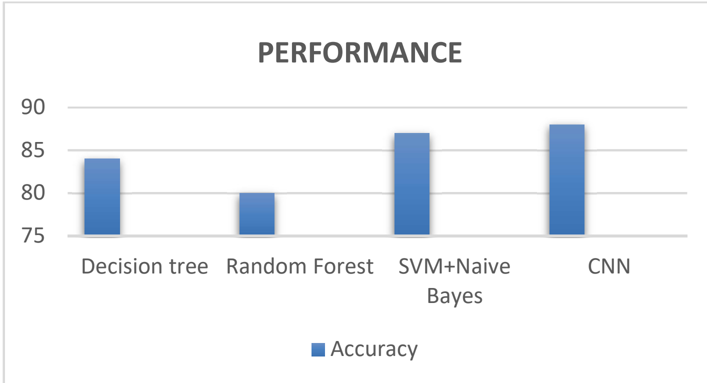

Fig.5. Performance Comparison of The Text Classification Models

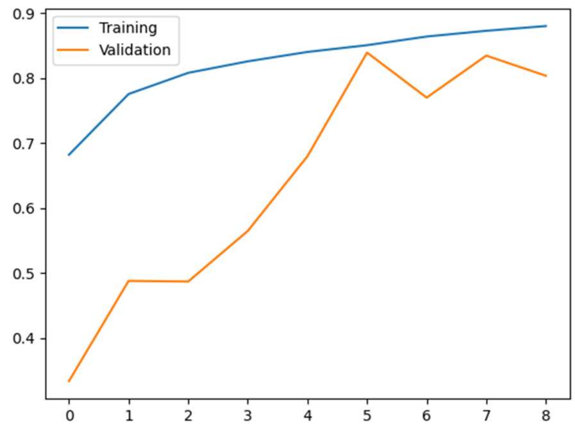

Fig.6. Training and Validation Accuracy Plot by Applying CNN

neurons are linked by the FC layer. A vector's output from the FC layer, which can be either +ve or -ve, is produced as the vector passes through.

The activation function softmax can be used to categorize the diverse classes of the FC layer. The softmax function calculates the probability value for each class and output.

9 Results and Discussion

To compare with our CNN models, Decision Tree (DT), SVM+Naive Bayes, and Random Forest (RF) were used. The SVM+Naive Bayes technique is an abbreviation for the Naive Bayes methodology for calculating the weight and the SVM method for classification.

Using the method allows for basic data processing, such as stop-word support, lemmatization, and deletion. Combining the two could be expected to improve classification performance compared to each individual's performance. Yet the purpose of the study is to determine why CNN does so well in comparison to others.

All words found in the training set are now included in list-BOW for non-deep methods. We reorganise the corpus data as a list of tuples, where the first element is the word tokens of the document and the second element is the label of the document, i.e., sentiment labels. Both the number of documents and the quantity of words make up a corpus.

The size of the corpus determines how much of the training and testing set is used. We employ naive bag of word text vectorization. The fact that this dataset has 330k reviews, which requires a lot of computing power, is a serious issue. We tested numerous settings to optimize the CNN model suggested in this research.

Except for the output layer, which used a softmax function, all layers used the Rectified Linear Unit (ReLU) as an activation function. We experimented with several dataset combinations and found that the SVM with the NB kernel was our purpose's most effective augmented model.

Thus, to compare the CNN with other models, it was strengthened using SVM. The proposed CNN models, conventional machine-learning models, and other cutting-edge methods all used the dataset.

The binary classification experiment findings, where each cell's two values represent the "positive" and "negative," respectively. Depending on the opinion of the patient's family members, each review in this study was categorized as either favourable or negative.

Model deep learning We discuss multiple deep learning architectures for sentiment analysis of drug reviews in this section. In the convolution layer of the CNN architecture, various filters work sliding along the word embedding matrix of each drug review, generating a mapping of the review features as an output. As a linguistic model for drug reviews, BERT (Bidirectional Encoder Representations from Transformers) is used.

The ability of BERT to generate contextualized word embeddings is by far its greatest advantage over Word2Vec models because, unlike directional models, which read the text input sequentially (either from left to right or from right to left), the Transformer encoder reads the entire sequence of words at once.

As a result, it is referred to as bidirectional, even though it would be more accurate to refer to it as non-directional [16]. Because of this trait, the model can understand a word's context by considering all of its surroundings (left and right of the word). The CNN model's accuracy rating is 88.02%.

While the random forest classifier performed poorly, results from the decision tree and SVM+Naive Bayes classifiers are comparable. Examining various algorithms to determine which algorithm provides the best accuracy, we have examined many algorithms on the dataset. Decision tree, Random Forest, and SVM+Naive Bayes are the algorithms that are employed.

The dataset was trained using the algorithm that provided the highest accuracy. Analysis and Classification of Emotions Following training with the dataset, the reviews were parsed to identify the keywords that denote positive and negative terms. The polarity, which determines the reviews' sentiment, is assigned to each review.

The CNN classifier categorizes the reviews for each drug used to treat medical ailments. It categorizes the reviews for each medication connected to the ailment as either favourable or bad. The CNN classifier was trained on the dataset.

Classifiers To create a classifier that could anticipate the sentiment, various deep-learning classification methods were applied. Only deep-learning classification methods with shorter training times and quicker predictions were chosen.

Precision(p), recall(r), and accuracy were the criteria used to evaluate the anticipated sentiment. Let the letter be:

Tp = True positives or instances where the program accurately anticipated the sentiment of positivity,

Tn = True negative instances or situations when the model accurately anticipated the negative class,

Fp = False positives or instances where a model incorrectly forecasted the positive class,

Fn = False negatives or instances where a model incorrectly predicted the negative class,

The equations below demonstrate precision, recall, accuracy, and F1 score.

Precision can be calculated using the formula TP/(Tp+Fp).

Tp/(Tp+Fn) is a formula that can be used to calculate recall.

The formula for the F1 score is 2(p*r)/(p+r), where p stands for precision and r for recall.

Based on the aforementioned chart, the accuracy calculation is (Tp+Tn)/(Tp+Fp+Fn+Tn), or the total number of true positive and true negative cases divided by the total number of cases.

The explanation for this is that, as shown in Table 2, the Convolutional Neural Network model was already adequate to attain a good presentation. When compared to a machine learning model, the accuracy of a convolutional neural network is noticeably improved (Fig. 5).

Every one of the four ways yields good results. We merely added each method's best-predicted outcome to the recommendation framework. Ensure that the various expected findings are properly assembled for the best results and understanding.

This paper only aims to demonstrate the methods for classifying data and extracting sentiment to create a recommender system. We think that the CNN model's ability to do so is what causes the performance discrepancy.

Additionally, the suggested network outperformed cutting-edge deep learning algorithms. The training and validation accuracy through the training epochs is displayed in Figure 6.

10 Conclusion and Future Work

This study investigated the sentiment analysis of drug evaluations to build a recommender system using different deep-learning approaches. In this research, constructed a CNN to classify sentiment. The categorization accuracy using models was 88.02%. The extra feature representations result in features that are very good at differentiating between various sentiment classes.

In experiments using big medical datasets, sentiment prediction accuracy has greatly improved. The framework also generates a precise sentiment time series that closely resembles how patients generally see a variety of medications.

The recommended framework, therefore, enhances event recollection and event recognition speed, which facilitates the detection of adverse drug occurrences, our method has been assessed concerning adverse pharmacological effects.

Although the methodology has only been tested concerning adverse drug occurrences, it is broad enough to be used with datasets from other pharmacies' items. The findings have significant ramifications for medical intelligence and big data analytics.

To determine the best approach for delivering big data services in the cloud while taking uncertainty into account for a better diagnosis concerning the patient facial recognition method, future research will evaluate the effectiveness of the proposed framework using additional AI-based and deep learning algorithms.

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