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Google Playstore Reviews Prediction Using ML And NLP

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Abstract— Play Store is Google's official pre-installed app store on Android-certified devices. It provides access to content on the Google Play Store, including apps, books, magazines, and music, movies, and television programs. Google play store allow the user to download a mobile application and user get inspired by the rating and reviews of the mobile app. A recent study analyzes that user preferences, user opinion for improvement, user sentiment about particular feature and detail with descriptions of experiences are very useful for an application development. The aim is to classify the Google app reviews based on supervised machine learning techniques (SMLT).The analysis of dataset by supervised machine learning technique (SMLT) to capture several information's like, variable identification, univariate analysis, bi-variate and multi-variate analysis, missing value treatments and analyze the data validation, data cleaning/preparing and data visualization will be done on the entire given dataset. To propose a machine learning-based method to classify the Google play store reviews results in the form of positive, neutral or negative best accuracy from comparing supervise classification machine learning algorithms. Millions of mobile apps are available in app stores, such as Apple's App Store and Google Play. For a mobile app it would be increasingly challenging to stand out from the enormous competitors and become prevalent among users. Good user experience and well-designed functionalities are the keys to a successful app. To achieve this, popular apps usually schedule their updates frequently. If we can capture the critical app issues faced by users in a timely and accurate manner, developers can make timely updates, and good user experience can be ensured.

Keywords: ***Google Playstore, Machine Learning, Natural Learning Process, SMLT techniques.***

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I. INTRODUCTION

MOBILE apps keep gaining popularity over the last few years. According to Statista the global mobile internet user penetration in 2016 has exceeded half the world's population. During the third quarter of 2018, Android users were able to choose from 2.1 million apps, while Apple's App Store provided almost 2 million apps. While users have a large number of products to choose from, the apps are facing immensely fierce competition to survive. The popular mobile app stores, such as Google Play and App Store, use the star-rating mechanism to gather users' ratings and feedback. The feedback and ratings can impact an app's ranking on these stores, and further influence its discovery and trial. A survey in reported that only 15%∼50% of the users would consider downloading a lowrated app, while for the high-rated apps, the ratio reached 96%. Thus, ensuring good user experience and keeping users engaged can help maintain high download numbers and increase benefits to app developers.

Recent studies showed that frequently updated apps could benefit in terms of increase in ranking. This is the case since the popular app stores factor in the freshness of an app in the ranking process. Additionally, app updates can also improve user experience. Specifically, McIlroy et al. found that the rationale behind updates is often related to bug-fixing (63% of the time), new features (35%), and feature improvement (30%). However, not every update can definitely lead to positive user experience and high ranking. For example, the updated Android and iOS versions of Skype released in June 2017 received a flood of complaints as the new design removed the key functionality andfeatures available in the older version, such as the visibility of online friends .As a result, its user rating on the App Store plunged from 4.5 to 1.5 stars shortly after the update. Such situations are not unusual, and can cause customer churn and losses to app developers. The losses could be limited if the issues were recognized timely. In thi s work, we aim at accurately detecting emerging app issues by analyzing user feedback. IDEA is one of the most recent works that can be directly applied to detect emerging issues/topics from user feedback. IDEA takes user reviews distributed in consecutive app versions as input, and outputs emerging app issues in the level of phrases and sentences. A modified online topic modeling approach is utilized to infer topics of the text corpus in consecutive time periods. Finally, IDEA employs a topic labeling approach to automatically prioritize the phrases/sentences that are semantically representative of the topics. The prioritized phrases/sentences are regarded as descriptions of emerging issues. Although the approach achieves reasonable performance, it has several limitations in accurately detecting emerging app issues as it does not consider the following characteristics of user feedback and exists inefficiency during topic labeling

In this paper, we propose an iMproved EmeRging Issue deTection approach, named MERIT, to mitigate these limitations and more accurately detect emerging app issues. Different from the topic modeling approach in IDEA, where a topic is a probability distribution over single words, MERIT considers topics over a mixture of biterms. Here, a biterm is an unordered word-pair co-occurring in a short context

II. RELATED WORKS

A literature review is a body of text that aims to review the critical points of current knowledge on and/or methodological approaches to a particular topic. It is secondary sources and discuss published information in a particular subject area and sometimes information in a particular subject area within a certain time period. Its ultimate goal is to bring the reader up to date with current literature on a topic and forms the basis for another goal, such as future research that may be needed in the area and precedes a research proposal and may be just a simple summary of sources. Usually, it has an organizational pattern and combines both summary and synthesis.

Aspect-based sentiment analysis of scientific reviews souvic chakra [1] Scientific papers are complex and understanding the usefulness of these papers requires prior knowledge. Peer reviews are comments on a paper provided by designated experts on that field and hold a substantial amount of information, not only for the editors and chairs to make the final decision, but also to judge the potential impact of the paper. In this paper, we propose to use aspect-based sentiment analysis of scientific reviews to be able to extract useful information, which correlates well with the accept/reject decision. While working on a dataset of close to 8k reviews from ICLR, one of the top conferences in the field of machine learning, we use an active learning framework to build a training dataset for aspect prediction, which is further used to obtain the aspects and sentiments for the entire dataset.We show that the distribution of aspect-based sentiments obtained from a review is significantly different for accepted and rejected papers. We use the aspect sentiments from these reviews to make an intriguing observation, certain aspects present in a paper and discussed in the review strongly determine the final recommendation. As a second objective, we quantify the extent of disagreement among the reviewers refereeing a paper. We also investigate the extent of disagreement between the reviewers and the chair and find that the inter-reviewer disagreement may have a link to the disagreement with the chair. One of the most interesting observations from this study is that reviews, where the reviewer score and the aspect sentiments extracted from the review text written by the reviewer are consistent, are also more likely to be concurrent with the chair's decision.

ASAP: A Chinese Review Dataset Towards Aspect Category Sentiment Analysis and Rating Prediction Jiahao Bu1 , Lei Ren , Shuang Zheng , Yang Yang , Jingang Wang , Fuzheng Zhang , Wei Wu [2] Sentiment analysis has attracted increasing attention in e-commerce. The sentiment polarities underlying user reviews are of great value for business intelligence. Aspect category sentiment analysis (ACSA) and review rating prediction (RP) are two essential tasks to detect the fine-to-coarse sentiment polarities. ACSA and RP are highly correlated and usually employed jointly in real-world e-commerce scenarios. While most public datasets are constructed for ACSA and RP separately, which may limit the further exploitations of both tasks. To address the problem and advance related researches, we present a large-scale Chinese restaurant review dataset ASAP including 46, 730 genuinereviews from a leading online-to-offline (O2O) e-commerce platform in China.Besides a 5-star scale rating, each review is manually annotated according to its sentiment polarities towards 18 pre-defined aspect categories. We hope the release of the dataset could shed some light on the field of sentiment analysis. Moreover, we propose an intuitive yet effective joint model for ACSA and RP. Experimental results demonstrate that the joint model outperforms state-of-the-art baselines on both tasks, This paper presents ASAP, a large-scale Chinese restaurant review dataset towards aspect category sentiment analysis (ACSA) and rating prediction (RP). ASAP consists of 46, 730 restaurant user reviews with star ratings from a leading e-commerce platform in China.Each review is manually annotated according to its sentiment polarities on 18 fine-grained aspect categories. Besides evaluations of ACSA and RP models on ASAP separately, we also propose a joint model to address ACSA and RP synthetically, which outperforms other state-ofthe-art baselines considerably. we hope the release of ASAP could push forward related researches and applications

Sentiment Analysis for Amazon Products using Isolation Forest S. Salmiah, Dadang Sudrajat, N. Nasrul, Tuti Agustin, Nisa Hanum Harani, Phong Thanh Nguyen [3] To text examination for efficiently recognize, evaluate, study full of affective states, extricate use of normal language preparing is known as Sentiment Analysis. The applications in which use advertising to client administration to clinical drug like applications use sentiment analysis on the web and webbased social networking, human services materials and audits and study reactions. Many sites like Amazon urged users to post the review of the product on its site. But Amazon provides the limit ofcontent to post the reviews. For different applications the review helps to analyze the product although the review for several products will different. This research works on the data that is recovered from Amazon and apply and expand the present work in the field of sentiment analysis and natural language processing.The work uses Machine Learning algorithms and characterize into positive or negative surveys To content assessment for effectively perceive, assess, study loaded with full of feeling states, remove utilization of typical language getting ready is known as Sentiment Analysis. The applications where use promoting to customer organization to clinical medication like applications use supposition examination on the web and online person to person communication, human administrations materials and reviews and study responses. Numerous locales like Amazon encouraged clients to post the audit of the item on its site.Yet, Amazon gives the farthest point of substance to post the surveys. For various applications the audit breaks down the item despite the fact that the survey for a few items will extraordinary. This exploration takes a shot at the information that is recouped from Amazon and applies and extends the present work in the field of opinion investigation and common language preparing. The work uses Machine Learning calculations and describe into positive or negative studies

A Review on Sentiment Analysis Approaches Ashwini Patil,Shiwani Gupta [4] Sentiment analysis has become one of the most profound research areas with the increasing growth of social media on web. Nowadays, millions of users exchange their views, ideas, expressions, feelings,opinions on social media like twitter and Facebook. Sentiment analysis or opinion mining mainly focuses on classification and prediction of people's opinion about a specific target. It involves classifying text documents or sentences based on the opinion expressed being positive or negative about a given topic.The task of sentiment analysis seems similar to text classification, but it faces many challenges that have motivated focused research in this domain. To automate the sentiment analysis task, various machine learning and lexicon based techniques have been proposed in literature. Though these techniques have been widely used for sentiment classification, these techniques failed to achieve the best results in terms of accuracy and to resolve all the challenges. So, there is need to develop new automated techniques that resolve all the challenges and give the best performance.

Sentiment analysis using product review data Xing Fang and Justin Zhan [5] Sentiment analysis or opinion mining is one of the major tasks of NLP (Natural Language Processing). Sentiment analysis has gain much attention in recent years. In this paper, we aim to tackle the problem of sentiment polarity categorization, which is one of the fundamental problems of sentiment analysis.A general process for sentiment polarity categorization is proposed with detailed process descriptions. Data used in this study are online product reviews collected from Amazon.com. Experiments for both sentence-level categorization and review-level categorization are performed with promising outcome.Sentiment analysis or opinion mining is a field of study that analyzes people's sentiments, attitudes, or emotions towards certain entities. This paper tackles a fundamental problem of sentiment analysis, sentiment polarity categorization. Online product reviews from Amazon.com are selected as data used for this study.A sentiment polarity categorization process has been proposed along with detailed descriptions of each step. Experiments for both sentence-level categorization and review-level categorization have been performed

III. IMPLEMENTATION

A. Existing System

Good user experience and well-designed functionalities are the keys to a successful app. To achieve this, popular apps usually schedule their updates frequently. If we can capture the critical app issues faced by users in a timely and accurate manner, developers can make timely updates, and good user experience can be ensured. To ensure good user experience and maintain high-quality apps, identifying emerging issues in a timely and accurate manner is critical. In this paper, we propose a novel topicmodeling-based framework named MERIT for detecting emerging issues by analyzing online app reviews. MERIT improves the state-of-the-art method by better modeling of short review texts, jointly modeling topics and sentiment, and using word embeddings to better interpret topics.

B. Proposed System

Machine learning supervised classification algorithms will be used to give thE given dataset and extract patterns, which would help in classifying the reviews, thereby helping the apps for making better decisions of their features in the future.

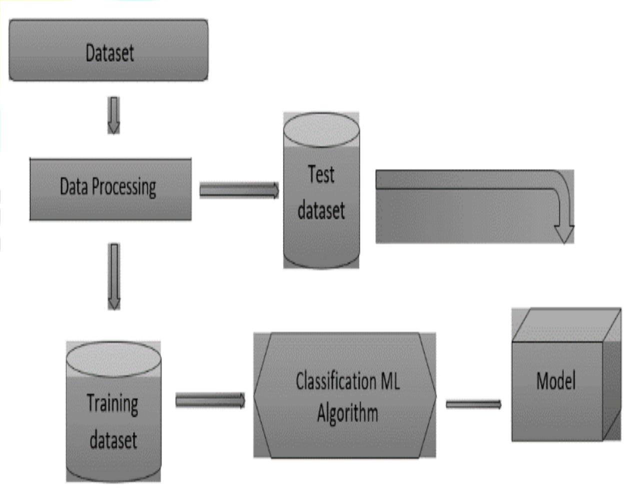

Fig 1. Proposed System

C. Dataset Collection

In this section of the report, user will load in the data, check for cleanliness, and then trim and clean user dataset for analysis.The data set collected for classifying the given data is split into Training set and Test set. Generally, 70:30 percentage are applied to split the Training set and Test set. The Data Model which was created using the SMLT is applied on the Training set and based on the test result accuracy, Test set prediction is done.

D. Architecture of Proposed Method

A **sys**tem architecture is the conceptual model that defines the structure, behavior, and more views of a system. An architecture description is a formal description and representation of a system organized in a way that supports reasoning about the structures and behaviors of the system.

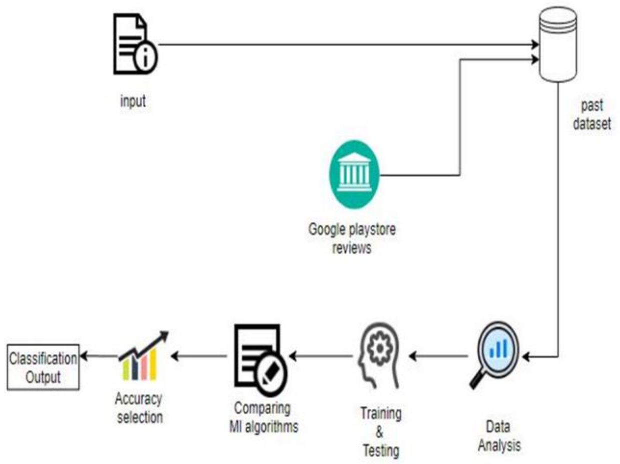

Fig 2. Architecture of Proposed System

E. Data Preprocessing

Validation techniques in machine learning are used to get the error rate of the Machine Learning (ML) model, which can be considered as close to the true error rate of the dataset. If the data volume is large enough to be representative of the population, you may not need the validation techniques. However, in real-world scenarios, to work with samples of data that may not be a true representative of the population of given dataset. To finding the missing value, duplicate value and description of data type whether it is float variable or integer. The sample of data used to provide an unbiased evaluation of a model fit on the training dataset while tuning model hyper parameters.

The evaluation becomes more biased as skill on the validation dataset is incorporated into the model configuration. The validation set is used to evaluate a given model, but this is for frequent evaluation. It as machine learning engineers use this data to fine-tune the model hyper parameters. Data collection, data analysis, and the process of addressing data content, quality, and structure can add up to a time-consuming to-do list. During the process of data identification, it helps to understand your data and its properties; this knowledge will help you choose which algorithm to use to build your model.

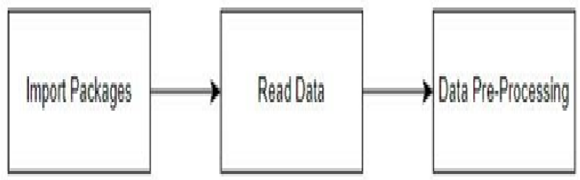

Fig 3. Data Preprocess

A number of different data cleaning tasks using Python's Pandas library and specifically, it focus on probably the biggest data cleaning task, missing values and it able to more quickly clean data. It wants to spend less time cleaning data, and more time exploring and modeling. Some of these sources are just simple random mistakes. Other times, there can be a deeper reason why data is missing. It's important to understand these different types of missing data from a statistics point of view. The type of missing data will influence how to deal with filling in the missing values and to detect missing values, and do some basic imputation and detailed statistical approach for dealing with missing data. Before, joint into code, it's important to understand the sources of missing data.

Design is the first step in the development phase for any techniques and principles for the purpose of defining a device, a process or system in sufficient detail to permit its physical realisation. Once the software requirements have been analysed and specified the software design involves three technical activities: design, coding, implementation and testing that are required to build and verify the software. The design activities are of main importance in this phase, because in this activity, decisions ultimately affecting the success of the software implementation and its ease of maintenance are made. These decisions have the final bearing upon reliability and maintainability of the system. Design is the only way to accurately translate the customer requirements into finished software or a system. Design is the place where quality is fostered in development. Software design is a process through which requirements are translated into a representation of software. Preliminary design is concerned with the transformation of requirements into data.

Importing the library packages with loading given dataset. To analyzing the variable identification by data shape, data type and evaluating the missing values, duplicate values. A validation dataset is a sample of data held back from training your model that is used to give an estimate of model skill while tuning model's and procedures that you can use to make the best use of validation and test datasets when evaluating your models. Data cleaning / preparing by rename the given dataset and drop the column etc. to analyze the uni-variate, bi-variate and multi-variate process. The steps and techniques for data cleaning will vary from dataset to dataset. The primary goal of data cleaning is to detect and remove errors and anomalies to increase the value of data in analytics and decision making.

```
In [10]: #To describe the dataframe
         df.describe()
```

Out[10]:

	Sentiment_Polarity	Sentiment_Subjectivity
count	37427.000000	37427.000000
mean	0.182171	0.492770
std	0.351318	0.259904
min	-1.000000	0.000000
25%	0.000000	0.357143
50%	0.150000	0.514286
75%	0.400000	0.650000
max	1.000000	1.000000

Fig 4. Preparing Process

F. Data Visualization

Data visualization is an important skill in applied statistics and machine learning. Statistics does indeed focus on quantitative descriptions and estimations of data. Data visualization provides animportant suite of tools for gaining a qualitative understanding. This can be helpful when exploring and getting to know a dataset and can help with identifying patterns, corrupt data, outliers, and much more. With a little domain knowledge, data visualizations can be used to express and demonstrate key relationships in plots and charts that are more visceral and stakeholders than measures of association or significance. Data visualization and exploratory data analysis are whole fields themselves and it will recommend a deeper dive into some the books mentioned at the end.

Fig 5. Data Visualization

Sometimes data does not make sense until it can look at in a visual form, such as with charts and plots. Being able to quickly visualize of data samples and others is an important skill both in applied statistics and in applied machine learning. It will It will discover the many types of plots that you will need to know when visualizing data in Python and how to use them to better understand your own data.

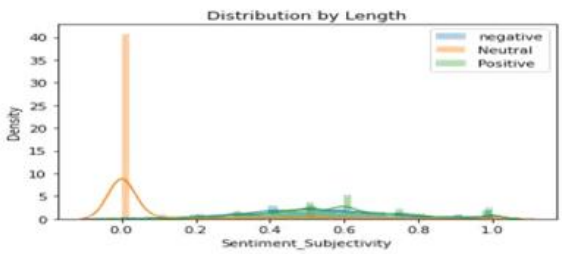

Fig 6. Exploration data analysis of Visualization

G. Performance Analysis

Pre-processing refers to the transformations applied to our data before feeding it to the algorithm. Data Preprocessing is a technique that is used to convert the raw data into a clean data set. In other words, whenever the data is gathered from different sources it is collected in raw format which is not feasible for the analysis. To achieving better results from the applied model in Machine Learning method of the data has to be in a proper manner. Some specified Machine Learning model needs information in a specified format, for example, Random Forest algorithm does not support null values. Therefore, to execute random forest algorithm null values have to be managed from the original raw data set. And another aspect is that data set should be formatted in such a way that more than one Machine Learning and Deep Learning algorithms are executed in given dataset.

- **False Positives (FP):** A person who will pay predicted as defaulter. When actual class is no and predicted class is yes. E.g. if actual class says this passenger did not survive but predicted class tells you that this passenger will survive.
- **False Negatives (FN):** A person who default predicted as payer. When actual class is yes but predicted class in no. E.g. if actual class valueindicates that this passenger survived and **predicted** class tells you that passenger will die.
- **True Positives (TP):** A person who will not pay predicted as **defaulter. These are the correctly predicted positive values which means that the value of actual class is yes and the value of predicted class is also yes. E.g. if actual class value indicates that this passenger survived and predicted class tells you the same thing.**
- **True Negatives (TN):** A person who default predicted as payer. These are the correctly predicted negative values which means that the value of actual class is no and value of predicted class is also no. E.g. if actual class says this passenger did not survive and predicted class tells you the same thing.

It is important to compare the performance of multiple different machine learning algorithms consistently and it will discover to create a test harness to compare multiple different machine learning algorithms in Python with scikit-learn. It can use this test harness as a template on your own machine learning problems and add more and different algorithms to compare. Each model will have different performance characteristics. Using resampling methods like cross validation, you can get an estimate for how accurate each model may be on unseen data. It needs to be able to use these estimates to choose one or two best models from the suite of models that you have created. When have a new dataset, it is a good idea to visualize the data using different techniques in order to look at the data from different perspectives. The same idea applies to model selection. You should use a number of different ways of looking at the estimated accuracy of your machine learning algorithms in order to choose the one or two to finalize. A way to do this is to use different visualization methods to show the average accuracy, variance and other properties of the distribution of model accuracies.

In the next section you will discover exactly how you can do that in Python with scikit-learn. The key to a fair comparison of machine learning algorithms is ensuring that each algorithm is evaluated in the same way on the same data and it can achieve this by forcing each algorithm to be evaluated on a consistent test harness. The K-fold cross validation procedure is used to evaluate each algorithm, importantly conFigd with the same random seed to ensure that the same splits to the training data are performed and that each algorithm is evaluated in precisely the same way.

Before that comparing algorithm, Building a Machine Learning Model using install Scikit-Learn libraries. In this library package have to done preprocessing, linear model with logistic regression method, cross validating by KFold method, ensemble with random forest method and tree with decision tree classifier. Additionally, splitting the train set and test set. To predicting the result by comparing accuracy.

Logistic regression algorithm also uses a linear equation with independent predictors to predict a value. The predicted value can be anywhere between negative infinity to positive infinity. It need the output of the algorithm to be classified variable data. Higher accuracy predicting result is logistic regression model by comparing the best accuracy.

True Positive Rate(TPR) = TP / (TP + FN)

False Positive rate(FPR) = FP / (FP + TN)

Accuracy: The Proportion of the total number of predictions that is correct otherwise overall how often the model predicts correctly defaulters and non-defaulters.

Accuracy calculation:

Accuracy = (TP + TN) / (TP + TN + FP + FN)

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The system has been implemented as different modules. Software is divided into separately named and addressable components called modules that are integrated to satisfy problem requirements.

```
Train on 29941 samples, validate on 7486 samples
Epoch 1/1
29941/29941 [==============================] - 502s 17ms/step - loss: 0.5294 - accuracy: 0.7852 - precision: 0.6916 - recall:
0.4421 - val_loss: 0.4646 - val_accuracy: 0.8064 - val_precision: 0.6328 - val_recall: 0.8516

]: <keras.callbacks.callbacks.History at 0x144d9a69e80>
```

Fig 7. Deep Learning RNN

```
X_train.shape: (28070, 100)
X_test.shape: (9357, 100)
y_train.shape: (28070, 3)
y_test.shape: (9357, 3)
Train on 28070 samples, validate on 9357 samples
Epoch 1/30
28070/28070 [==============================] - 71s 3ms/step - loss: 0.6198 - accuracy: 0.7375 - precision: 0.7622 - recall: 0.8
509 - val_loss: 0.5043 - val_accuracy: 0.7919 - val_precision: 0.8319 - val_recall: 0.9259
Epoch 2/30
28070/28070 [==============================] - 68s 2ms/step - loss: 0.4733 - accuracy: 0.8078 - precision: 0.8645 - recall: 0.8
715 - val_loss: 0.4241 - val_accuracy: 0.8309 - val_precision: 0.8903 - val_recall: 0.9041
Epoch 3/30
28070/28070 [==============================] - 69s 2ms/step - loss: 0.4216 - accuracy: 0.8313 - precision: 0.8830 - recall: 0.8
859 - val_loss: 0.3906 - val_accuracy: 0.8464 - val_precision: 0.9268 - val_recall: 0.8853
Epoch 4/30
28070/28070 [==============================] - 69s 2ms/step - loss: 0.3836 - accuracy: 0.8484 - precision: 0.9003 - recall: 0.8
997 - val_loss: 0.4050 - val_accuracy: 0.8373 - val_precision: 0.9597 - val_recall: 0.8310
Epoch 5/30
28070/28070 [==============================] - 70s 2ms/step - loss: 0.3520 - accuracy: 0.8616 - precision: 0.9098 - recall: 0.9
084 - val_loss: 0.3880 - val_accuracy: 0.8477 - val_precision: 0.9414 - val_recall: 0.8790
Epoch 6/30
28070/28070 [==============================] - 70s 2ms/step - loss: 0.3217 - accuracy: 0.8745 - precision: 0.9201 - recall: 0.9
176 - val_loss: 0.3196 - val_accuracy: 0.8773 - val_precision: 0.9107 - val_recall: 0.9408
```

Fig 8. Training and Testing Data Split

```
Accuracy result ofDecision Tree Classifier  is: 100.0

Classification report of Decision Tree Classifier : Results:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      2481
           1       1.00      1.00      1.00      8748

    accuracy                           1.00     11229
   macro avg       1.00      1.00      1.00     11229
weighted avg       1.00      1.00      1.00     11229

Confusion Matrix result of Decision Tree Classifier : is:
 [[2481    0]
 [   0 8748]]

Sensitivity :  1.0

Specificity :  1.0
```

Fig 8. Decision Tree Classifier

Out[22]:

	App	Translated_Review	Sentiment	Sentiment_Polarity	Sentiment_Subjectivity
0	0	8865	2	6194	2521
1	0	22964	2	4396	311
3	0	26302	2	5342	4478
4	0	1986	2	6194	358
5	0	2066	2	6194	358

Fig 9. Sentiment Analysis

```
Reading GloVe: 400000it [00:15, 25181.09it/s]
tracking <tf.Variable 'Variable:0' shape=() dtype=int32, numpy=0> tp
tracking <tf.Variable 'Variable:0' shape=() dtype=int32, numpy=0> fp
tracking <tf.Variable 'Variable:0' shape=() dtype=int32, numpy=0> tp
tracking <tf.Variable 'Variable:0' shape=() dtype=int32, numpy=0> fn
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_1 (Embedding)      (None, 100, 100)          2208500
_________________________________________________________________
lstm_1 (LSTM)                (None, 128)               117248
_________________________________________________________________
dropout_1 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_1 (Dense)              (None, 3)                 387
=================================================================
Total params: 2,326,135
Trainable params: 117,635
Non-trainable params: 2,208,500
_________________________________________________________________
```

Fig 10. LSTM Performance

V. CONCLUSIONS

The analytical process started from data cleaning and processing, missing value, exploratory analysis and finally model building and evaluation. The best accuracy on public test set is higher accuracy score will be find out. This application can help to find the Prediction of Google play store review classification prediction.

VI. FUTURE ENHANCEMENT

Google play store review classification prediction to connect with cloud. To optimize the work to implement in Artificial Intelligence environment.

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