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An Efficient Machine Learning Technique for Rating Prediction of Google Play Store Apps

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***Abstract*— through the growing growth of mobile apps on Google Play Store, reliable app rating projections are crucial. Predictions help consumers choose and developers improve app quality. This study provides an effective machine learning method for Google Play Store app rating prediction. Our approach predicts app ratings using user reviews, app information (category, size, and version), and developer updates using Random Forest, Gradient Boosting, and Neural Networks. Preprocessing includes missing values, feature normalization, and user review sentiment analysis. Key app rating criteria are identified via feature selection. Our experiments show that integrating sentiment analysis with app metadata improves prediction accuracy. Mean Absolute Error (MAE) and Root Mean Squared Error show that the suggested model outperforms established methods. The results help optimize app development and user pleasure by predicting ratings better.**

***Keywords*— Machine Learning (ML), App Rating Prediction, Google Play Store, Sentiment Analysis, App Metadata, Random Forest (RF).**

I. INTRODUCTION

Machine learning approaches are fundamental as far as we're concerned to deal with various issues. Machine learning has various applications in various viewpoints and has unbelievable progression potential. It is unsurprising that machine learning could set up ideal theories to explain its displays. Meanwhile, its abilities of solo learning will be improved since there is a lot of data in the world anyway adding names to all of them isn't important. It is also guessed that brain framework designs will end up being progressively eccentric with the objective that they can isolate every one of the more semantically significant features. Also, significant learning will solidify with help adjusting better and we can use these focal points to accomplish more tasks.

Figure 1: Mobile App

In the present situation we can see that mobile apps playing a significant job in any singular's life. It has been seen that the improvement of the mobile application publicize amazingly affects progressed development. Having said that, with the reliably creating adaptable application grandstand there is furthermore a prominent climb of compact application originators definitely achieving high as can be pay by the overall versatile application industry.

With tremendous test from wherever all through the globe, it is fundamental for a creator to understand that he is going on in the right heading. To hold this pay and their spot in the market the application creators might have to sort out some way to stick into their current position. The Google Play Store is seen to be the greatest application stage. It has been seen that notwithstanding the way that it makes in excess of two overlap the downloads than the Apple App Store yet makes simply a huge piece of the money stood out from the App Store. Along these lines, I scratched data from the Play Store to coordinate our assessment on it.

With the quick improvement of cutting edge cells, versatile applications (MobileApps) have ended up being essential bits of our lives. In any case, it is problematic as far as

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we're concerned to track with the reality and to comprehend everything about the apps as new applications are entering market every day. It is represented that Android1market accomplished an enormous part of 1,000,000 applications in September 2011. Beginning at now, 0.675 million Android applications are open on Google Play App Store. Such a ton of applications are apparently an exceptional entryway for clients to buy from a wide assurance expand. We trust flexible application clients consider online application overviews as an important effect for paid applications. It is pursuing for a likely client to examine every one of the scholarly comments and rating to make a decision. Furthermore, application engineers experience issues in finding how to further develop the application execution reliant upon as a rule alone and would benefit by figuring out the an enormous number of printed comments.

GOOGLE PLAY STORE AND MOBILE APP

Google Play, also known as the Google Play Store and Android Market, is a computerized distribution system created by Google that serves as the primary app store for Android devices and its subsystems, as well as Chrome OS. It offers access to programs, music, books, movies, and TV programs, which can be accessed through an internet browser or through Android and iOS applications.

Applications can be downloaded for free or at a cost, and can be downloaded directly from the Google Play Store mobile app or by delivering the app to a device from the Google Play site. However, the store has faced security issues, with harmful software being accepted and transmitted to the store and downloaded by customers.

Google Play was launched on June 6, 2012, and has since been rebranded several times, including Google News, YouTube Music, and Google TV. In 2022, Play Games is set to remove its mobile app for an Android emulator for Windows, while Play Books will be replaced by an independent mobile app.

With over 3.5 million Android apps in 2017, Google Play has grown to over 3 million apps. Developers can distribute applications in over 150 countries, with delivery and labor costs taking 15% of the application cost, and designers receiving 85%. Customers can pre-order apps, movies, music, books, and games, and request discounts within 48 hours after purchase.

MACHINE LEARNING TECHNIQUES

Machine learning (ML) is the scientific study of algorithms and statistical models that PC systems employ to do a job without explicit instructions, utilizing patterns and deduction. It is part of computerized reasoning. Machine learning algorithms may anticipate or decide without being explicitly programmed by constructing a numerical model from sample information, called "preparing information". Machine learning algorithms are employed in many applications, such as email screening and PC vision, when conventional calculations are difficult or impossible.

Decision Tree

Decision trees are built using recursive partitioning to classify the data, i.e., by splitting the training set into distinct nodes, where one node contains all of or most of one category of the data. A decision tree can be constructed by considering the attributes one by one:

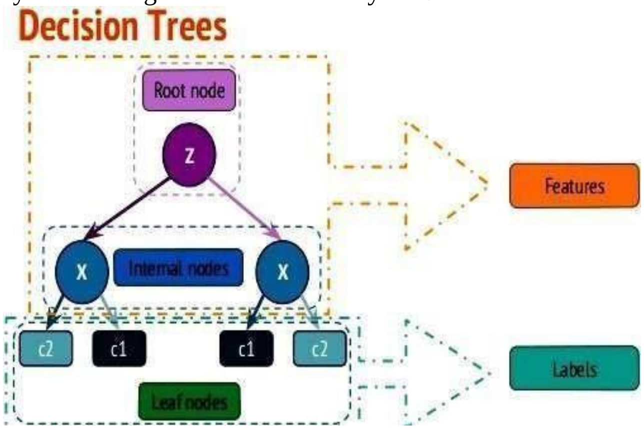

Figure 2: Decision tree

- First, choose an attribute from our dataset.
- Calculate the significance of the attribute in the splitting of the data.
- Next, split the data based on the value of the best attribute,
- Then go to each branch and repeat it for the rest of the attributes.
- After building this tree, you can use it to predict the class of unknown cases Decision trees are about testing an attribute and branching the cases based on the result of the test:

1. Each internal node corresponds to a test
2. Each branch corresponds to a result of the test
3. Each leaf node assigns a patient to a class

Naïve Bayes

In Naïve Bayes classifier is a supervised calculation which classifies the dataset on the basis of Bayes hypothesis. The Bayes hypothesis is a standard or the numerical idea that is used to get the likelihood is called Bayes hypothesis. Bayes hypothesis requires some free assumption and it requires autonomous variables which is the basic assumption of Bayes theorem.

Logistic Regression

Logistic regression is a classification calculation for unmitigated variables. Logistic regression is analogous to linear regression, however tries to foresee a clear cut or discrete objective field, such as 0 or 1, yes or no, and so forth., instead of a numeric one. Subordinate variables should be continuous. In the event that clear cut, they should be sham or marker coded. This means we need to transform them to some continuous worth. Logistic regression can be used for both twofold classification and multi-class classification. Sigmoid functions are a principle part of logistic regression.

K-Nearest Neighbors Algorithm (KNN)

The K-Nearest Neighbors is a calculation for supervised learning and is a classification calculation that takes a lot of named points and uses them to figure out how to name

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different points. This calculation classifies cases based on their similarity to different cases. In K- Nearest Neighbors, information points that are close to one another are said to be neighbors. K-Nearest Neighbors is based on this worldview. Thus, the distance between two cases is a measure of their dissimilarity. There are various ways to figure the similarity or conversely, the distance or dissimilarity of two information points. For instance, this should be possible using Euclidean distance.

Random Forest

Random Forest is an adaptable, easy to use machine learning calculation that produces, even without hyper-parameter tuning, an extraordinary result most of the time. It is also one of the most used algorithms, because its simplicity and the way that it tends to be used for both classification and regression tasks. Right now, will realize, how the random forest calculation works and several other significant things about it.

One major bit of leeway of random forest is, that it tends to be used for both classification and regression problems, which structure most of current machine learning systems.

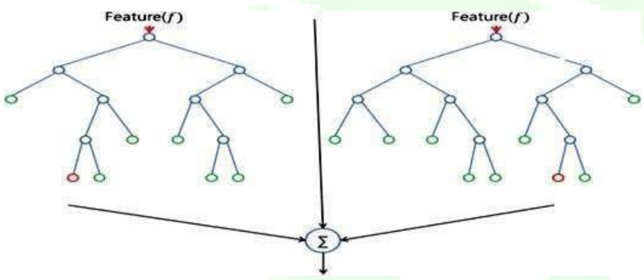

Figure 3: Random forest

II. LITERATURE REVIEW

R. Gomes et al.,[1] People need uses for daily exercise. As progress occurs, interest in its causes grows. We satisfy Google Play Store accomplishment requirements using classifiers. KNN and Irregular Backwoods were used to quantify application relapses using speculation, connection, and relapse metrics. This effort will create induction motors to predict usage appraisals using KNN and Irregular Backwoods relapse. The Arbitrary Woodland outperformed the KNN.

C. Zhu et al.,[2] Deep models for active visitor clicking percentage expectation need element insertion learning and element communication showing. Most deep CTR models suffer from these three difficulties. Include cooperations are either physically planned or listed. Second, all component associations communicate similarly. In most models, highlights with the same implanting size cause memory failure. For these three issues, we propose Programmed Connection Machine (Point) with three main parts, Element Communication Search, Collaboration Capability Search (Uncertainties), and Implanting Aspect Search, to naturally choose large component cooperations, fitting communication capabilities, and essential installing aspects in a bound together system. FIS recognizes various orders of fundamental element cooperations and prunes futile ones; Uncertainties chooses fitting connection capabilities for each component communication in a learnable manner; and EDS naturally assesses component implanting size. Disconnected examines three massive datasets to support Point's unmatched presentation. Point improves DeepFM model by 4.4% in CTR in a three-week online A/B test in a regular application market recommendation administration.

G. S. Bhat et al.,[3] Author introduce an ML-based asthma risk expectation device in this study. The whole tool is run on a phone as an m-healthcare app using Web of Things. External tools like top stream meters evaluate top expiratory stream rates, which are asthama risk markers. We use the PEFR to determine a link between indoor PM and outside climate. Compared to the highest stream value achieved by each participant, PEFR findings are divided into three classes: 'Green' (Safe), 'Yellow' (Moderate Gamble), and 'Red' (High Gamble). Convolutional brain organization engineering links indoor PM and climate data to PEFR values. The root mean square and mean outright error exactness measurements of the suggested technique are compared to cutting-edge deep brain organization (DNN) methods. Over other writing styles, these presentation metrics are favored for the suggested strategy. The whole process is an app on a phone. Data is collected using an IoT framework and Raspberry Pi. For asthma attack prevention, this device may be cost-effective.

Z. Wu et al.,[4] Application portrayal inspection has several uses in computer programming. Besides the unpredictability of regular language, insufficient consent semantics make it difficult to predict capabilities and authorized usages from program portrayals. More specifically, developers purposefully abridge application class functions due to the specified amount of characters, and consents are often over-guaranteed. These are the main reasons application portrayals provide false advantages in predicting authorizations. In earlier studies that didn't assist engineers improve application descriptions and avoid security risks, such unmentioned authorizations should be considered suspicious. We propose the FideDroid, a framework to identify class-based normal consents to balance core functionality while analyzing application depiction consistency. Our structure expands the named application depictions dataset for consent forecasting. FideDroid compares collected and used authorizations to identify suspicious and unnecessary ones based on anticipation. It helps developers refine application portrayals and track consent use. We found in our experiments on large real-world applications that class-based normal consents may cover additional unmentioned functionality without considering all conceivable authorizations during application depiction inspection. Three factors caused the discrepancy between portrayals and approved uses: 1) hard-copy human mediations; 2) bad consent processes; and 3) productive engineers. These findings will help designers enhance app depictions and consent use.

Z. Shen et al.,[5] This study predicts which apps a customer will access on her phone in the next timeframe. This data is essential for most mobile phone actions, such as application pre-stacking and content pre-reserving, to

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improve customer experience. It's hard to create a model that accurately captures the complex environment and anticipates several uses. DeepAPP, a deep support learning structure, learns a realistic model prophetic brain network from verified application usage data. Web-based refreshing is meant to adapt the foresight organization to time-varying application usage. To turn DeepAPP into a viable deep support learning framework, a setting portrayal strategy for complex relevant climate, an overall specialist to overcome information sparsity, and a lightweight customized specialist to reduce expectation time are addressed. Wide testing on an anonymous application use dataset show that DeepAPP has high accuracy (70.6% and review of 62.4%) and reduces cutting edge expectation season by 6.58 times. A 29-person field study shows DeepAPP may reduce application startup time.

Z. Xu et al.,[6] In the nick of time (JIT) bug expectation is a strong quality confirmation movement that detects if a code change will introduce problems into the portable program and provides concise feedback to pros for survey. Some flexible apps can't acquire enough identified bug information, thus cross-application models may be used. This paper proposes CDFE, a cross-trio deep element implanting approach for cross-application JIT bug expectation. The CDFE technique integrates a cutting-edge cross-trio misfortune capacity into a deep brain structure to learn cross-application data component representation. This unpleasant capacity works with cross-application learning and means to get acquainted with another element space to shorten the distance of commit events with identical names and expand the distance of commit cases with different markings. To reduce cross-application bug information inconsistency, this misfortune feature assigns larger loads to cross-application example matches than intra-application event matches. Our CDFE approach is tested on a benchmark bug dataset comprising 19 portable apps with two exertion aware pointers. Our CDFE method outperforms 14 conventional techniques in 342 cross-application matches.

III. PROBLEM IDENTIFICATION

T The mobile app developing grows rapidly. The customer gives the reviews after using the app. The mobile app developers can understand the target audience easily.

- Meeting user requirements.
- Choosing the operating system.
- Choosing the development platform.
- Security.

After developing and using the app, customer rating is very useful to success the app. Therefore during the literature survey some of the observation is carried out, which is as followings-

- Low accuracy rate of true data prediction from given dataset.
- Using traditional System Analysis alone not sufficient for proper feature extraction.
- More classification error.
- No adaptive approach to prediction of true rating of apps.
- Sensitivity, Specificity, Precision, Recall and F measure values is not good optimized.

IV. PROPOSED METHODOLOGY

Proposed Methodology

The main contribution of this research is as followings-

- To collect google play store dataset.
- To proposed and implement KNN and Random forest classification algorithm for review prediction.
- To simulate proposed method on spyder python 3.7 software.
- To calculate various parameters like Precision, Recall, F-1, Accuracy, Sensitivity, Error rate and Specificity.
- To compare the simulation results with the previous work.

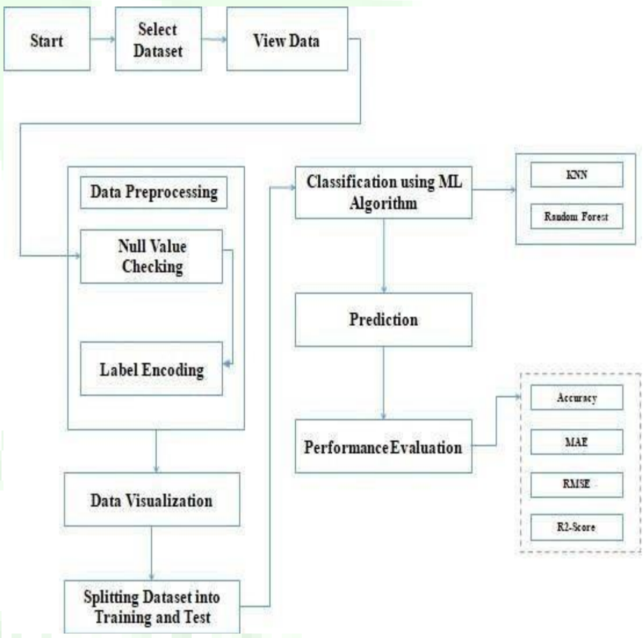

Figure 4: Flow Chart

Steps-

1. Firstly, download the google play store mobile app dataset from kaggle website, which is a large dataset provider and machine learning repository Provider Company for research.
2. Now apply the preprocessing of the data, here handing the missing data, removal null values.
3. Now extract the data features and evaluate in dependent and independent variable.
4. Now apply the classification method based on the machine learning (KNN) and random forest regression (RF) approach.
5. Now generate confusion matrix and show all predicted class like true positive, false positive, true negative and false negative.

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Now calculate the performance parameters by using the standard formulas in terms of the precision, recall, F1_measure, accuracy and error rate.

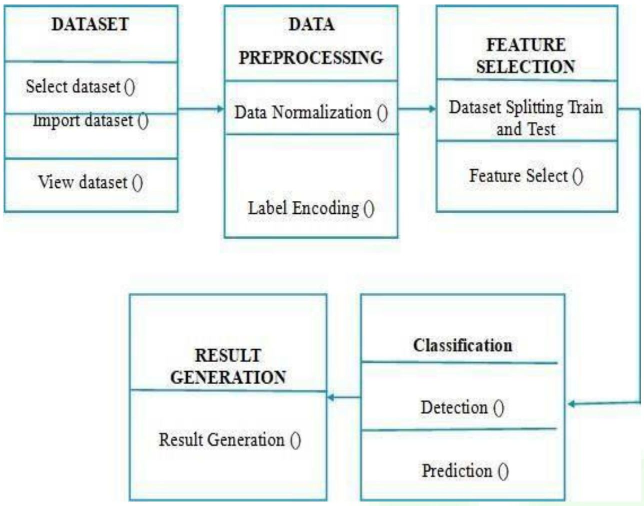

Figure 5: Class Diagram

METHODOLOGY

The system flaws, the recommended model is presented. This method classifies data using Google Play applications to improve classification accuracy. The Google Play store dataset is semi-structured or unstructured and includes a lot of unnecessary data. Vectorizing text is necessary for supervised machine learning algorithm training. To do this, text must be transformed to numbers without losing information. Machine Learning Regressors (KNN and Random Forest) predict app rating. Classifier performance is assessed by accuracy, MAE, RMSE, and R2-Score.

The following steps is adopted to understand of the process of this research work-

- Data selection and loading
- Data Preprocessing
- Feature Selection
- Classification
- Prediction

Data Selection and Loading

The data selection is the process of selecting the data for predicting the depression patient emotion from the IoT smart home dataset. It contains the readings with a time span of 1 minute of house appliances in kW from a smart meter and weather conditions of that particular region.

Data Preprocessing

Data pre-processing is the process of removing the unwanted data from the dataset.

- Missing data removal
- Encoding Categorical data

Data Visualization

Exploratory data analysis is an approach of analyzing data sets to summarize their main characteristics, often using statistical graphics and other data visualization methods. A statistical model can be used or not, but primarily EDA is for seeing what the data can tell us beyond the formal modelling or hypothesis testing task.

Splitting Dataset into Train and Test Data

Data splitting is the act of partitioning available data into two portions, usually for cross- validate purposes. One portion of the data is used to develop a predictive model and the other to evaluate the model's performance. Separating data into training and testing sets is an important part of evaluating data mining models. Typically, when you separate a data set into a training set and testing set, most of the data is used for training, and a smaller portion of the data is used for testing.

Classification

Classification is a process related to categorization, the process in which ideas and objects are recognized, differentiated, and understood. The KNN and Random Forest classification algorithm is used for predicting the google play app ratings. KNN is easiest supervised machine learning algorithm. It’s the foremost basic machine learning algorithm you'll find on scikit-learn. With the assistance of KNN we will do pattern recognition and data processing. KNN defines the similarity. From the given dataset KNN finds common groups between attributes.

Random forest regression is applied to all the variables the results of random forest determine the importance of the entire variable and their influence on the rating. The results of random forest regression are evaluated using Mean Square Error. Random forest model is the first model that is applied to the dataset and the results of random forest classification are computed for a number of variables to find the importance of these variables.

V. Results

A SIMULATION SOFTWARE

Python—an interpreter, advanced, and useful programming language. Python's plan reasoning, developed by Guido van Rossum in 1991, emphasizes code clarity with significant whitespace. Its language builds and article-organized philosophy aim to help developers write clear, real code for small and large projects.

Python is constantly produced and trashed. It supports procedural, object-oriented, and utilitarian programming. Python is sometimes called a "batteries included" language due to its extensive standard library.

Python was considered a substitute for ABC in the late 1980s. Python 2.0, released in 2000, included rundown perceptions and a rubbish arrangement framework for social event reference cycles. Python 3.0, released in 2008, was a key correction of the language that isn't perfect, and many Python 2 code doesn't run on Python 3. Python 2, including Python 2.7.x, was officially halted on January 1, 2020 (originally planned for 2015), and security fixes and upgrades will no longer be provided. Python 3.5.x and beyond are supported after Python 2's end.

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Python translators support functioning frameworks. Software developers develop and maintain CPython, an open-source reference execution. The non-profit Python Programming Foundation manages Python and CPython development resources.

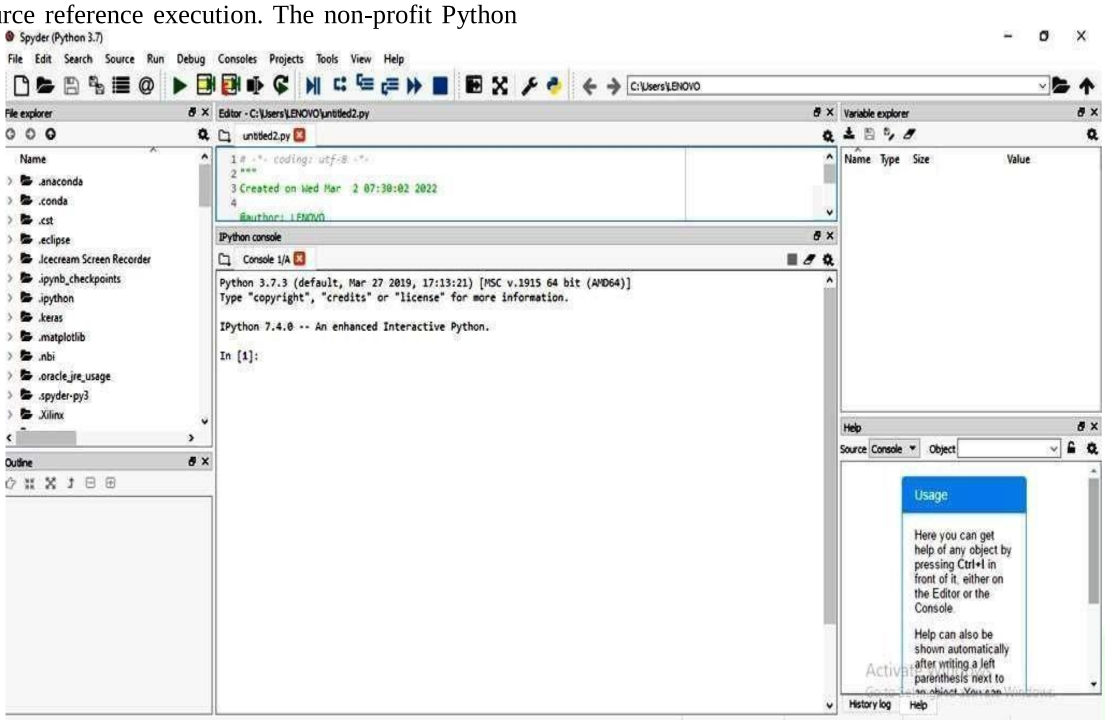

Figure 6: Snap shot of Spyder environment

RESULT AND ANALYSIS

The simulation starts from taking the dataset. In this dataset the various features value mention like app, category, rating reviews, size, installs type, price, content, rating, genres last updated, current ver, android ver.

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	App	Category	Rating	Reviews	Size	Installs	Type	Price	Content Rating	Genres	Last Updated	Current Ver	Android Ver
2	Photo Editor & Candy	ART_AND_DESIGN	4.1	159	19M	10,000+	Free	0	Everyone	Art & Design	January 7, 2018	1.0.0	4.0.3 and up
3	Coloring book moana	ART_AND_DESIGN	3.9	967	14M	500,000+	Free	0	Everyone	& Design;Pretend	January 15, 2018	2.0.0	4.0.3 and up
4	U Launcher Lite â€" FR	ART_AND_DESIGN	4.7	87510	8.7M	5,000,000+	Free	0	Everyone	Art & Design	August 1, 2018	1.2.4	4.0.3 and up
5	Sketch - Draw & Paint	ART_AND_DESIGN	4.5	215644	25M	50,000,000+	Free	0	Teen	Art & Design	June 8, 2018	Varies with device	4.2 and up
6	Pixel Draw - Number	ART_AND_DESIGN	4.3	967	2.8M	100,000+	Free	0	Everyone	: & Design;Creativ	June 20, 2018	1.1	4.4 and up
7	Paper flowers instruc	ART_AND_DESIGN	4.4	167	5.6M	50,000+	Free	0	Everyone	Art & Design	March 26, 2017	1	2.3 and up
8	Smoke Effect Photo N	ART_AND_DESIGN	3.8	178	19M	50,000+	Free	0	Everyone	Art & Design	April 26, 2018	1.1	4.0.3 and up
9	Infinite Painter	ART_AND_DESIGN	4.1	36815	29M	1,000,000+	Free	0	Everyone	Art & Design	June 14, 2018	6.1.61.1	4.2 and up
10	Garden Coloring Book	ART_AND_DESIGN	4.4	13791	33M	1,000,000+	Free	0	Everyone	Art & Design	eptember 20, 201	2.9.2	3.0 and up
11	Kids Paint Free - Draw	ART_AND_DESIGN	4.7	121	3.1M	10,000+	Free	0	Everyone	: & Design;Creativ	July 3, 2018	2.8	4.0.3 and up
12	Text on Photo - Fonte	ART_AND_DESIGN	4.4	13880	28M	1,000,000+	Free	0	Everyone	Art & Design	October 27, 2017	1.0.4	4.1 and up
13	Name Art Photo Edito	ART_AND_DESIGN	4.4	8788	12M	1,000,000+	Free	0	Everyone	Art & Design	July 31, 2018	1.0.15	4.0 and up
14	Tattoo Name On My P	ART_AND_DESIGN	4.2	44829	20M	10,000,000+	Free	0	Teen	Art & Design	April 2, 2018	3.8	4.1 and up
15	Mandala Coloring Boc	ART_AND_DESIGN	4.6	4326	21M	100,000+	Free	0	Everyone	Art & Design	June 26, 2018	1.0.4	4.4 and up
16	3D Color Pixel by Nun	ART_AND_DESIGN	4.4	1518	37M	100,000+	Free	0	Everyone	Art & Design	August 3, 2018	1.2.3	2.3 and up
17	Learn To Draw Kawaii	ART_AND_DESIGN	3.2	55	2.7M	5,000+	Free	0	Everyone	Art & Design	June 6, 2018	NaN	4.2 and up
18	Photo Designer - Writ	ART_AND_DESIGN	4.7	3632	5.5M	500,000+	Free	0	Everyone	Art & Design	July 31, 2018	3.1	4.1 and up
19	350 Diy Room Decor Ic	ART_AND_DESIGN	4.5	27	17M	10,000+	Free	0	Everyone	Art & Design	November 7, 2017	1	2.3 and up
20	FlipaClip - Cartoon an	ART_AND_DESIGN	4.3	194216	39M	5,000,000+	Free	0	Everyone	Art & Design	August 3, 2018	2.2.5	4.0.3 and up
21	ibis Paint X	ART_AND_DESIGN	4.6	224399	31M	10,000,000+	Free	0	Everyone	Art & Design	July 30, 2018	5.5.4	4.1 and up
22	Logo Maker - Small Bu	ART_AND_DESIGN	4	450	14M	100,000+	Free	0	Everyone	Art & Design	April 20, 2018	4	4.1 and up
23	Boys Photo Editor - Si	ART_AND_DESIGN	4.1	654	12M	100,000+	Free	0	Everyone	Art & Design	March 20, 2018	1.1	4.0.3 and up
24	Superheroes Wallpap	ART_AND_DESIGN	4.7	7699	4.2M	500,000+	Free	0	Everyone 10+	Art & Design	July 12, 2018	2.2.6.2	4.0.3 and up
25	Mcqueen Coloring pa	ART_AND_DESIGN	NaN	61	7.0M	100,000+	Free	0	Everyone	esign;Action & Ad	March 7, 2018	1.0.0	4.1 and up

googleplaystore

Figure 7: Original dataset in .csv file

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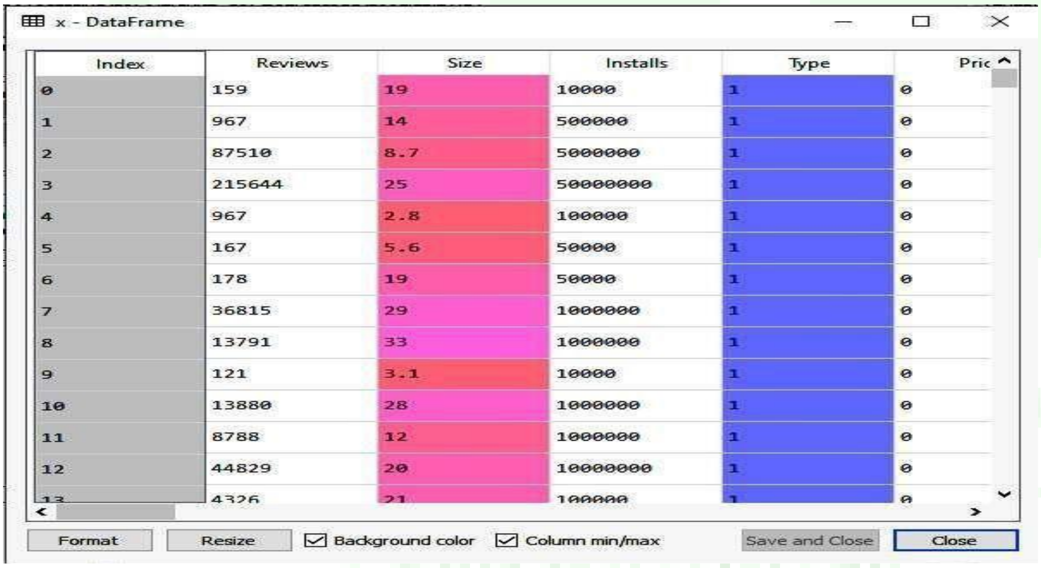
df - DataFrame

Index	Category	Rating	Reviews	Size	Insta
0	ART_AND_DESI...	4.1	159	19	10000
1	ART_AND_DESI...	3.9	967	14	500000
2	ART_AND_DESI...	4.7	87510	8.7	5000000
3	ART_AND_DESI...	4.5	215644	25	5000000(
4	ART_AND_DESI...	4.3	967	2.8	100000
5	ART_AND_DESI...	4.4	167	5.6	50000
6	ART_AND_DESI...	3.8	178	19	50000
7	ART_AND_DESI...	4.1	36815	29	1000000
8	ART_AND_DESI...	4.4	13791	33	1000000
9	ART_AND_DESI...	4.7	121	3.1	10000
10	ART_AND_DESI...	4.4	13880	28	1000000
11	ART_AND_DESI...	4.4	8788	12	1000000
12	ART_AND_DESI...	4.2	44829	20	1000000(
13	ART_AND_DESI...	4.6	4326	21	100000

Format Resize Background color Column min/max Save and Close Close

Figure 8: Dataset frame

Figure 8 is showing the dataset in the python environment. The dataset have various numbers of rows and column. The signal features name is also mentioned.



x - DataFrame

Index	Reviews	Size	Installs	Type	Pric
0	159	19	10000	1	0
1	967	14	500000	1	0
2	87510	8.7	5000000	1	0
3	215644	25	50000000	1	0
4	967	2.8	100000	1	0
5	167	5.6	50000	1	0
6	178	19	50000	1	0
7	36815	29	1000000	1	0
8	13791	33	1000000	1	0
9	121	3.1	10000	1	0
10	13880	28	1000000	1	0
11	8788	12	1000000	1	0
12	44829	20	10000000	1	0
13	4326	21	100000	1	0

Format Resize Background color Column min/max Save and Close Close

Figure 9: X label of data

Figure 9 is showing x label of dataset view, here the app size, number of installation, etc details are mention in the form of numeric.

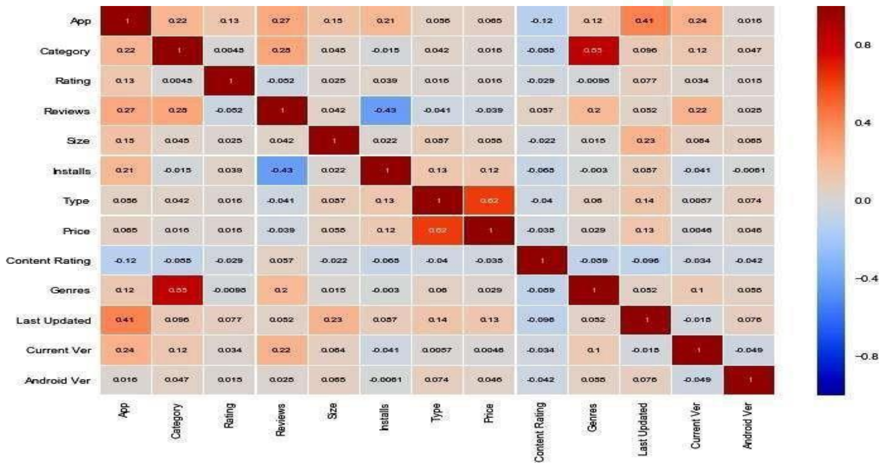


Figure 10: Heap map

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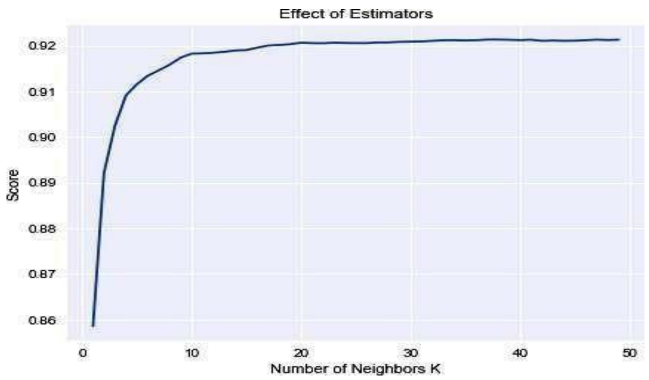

Figure 11: Effect of estimators-1

Figure is 11 is showing effect of the estimators. The number of neighbors is 50 then the score is more than 92%.

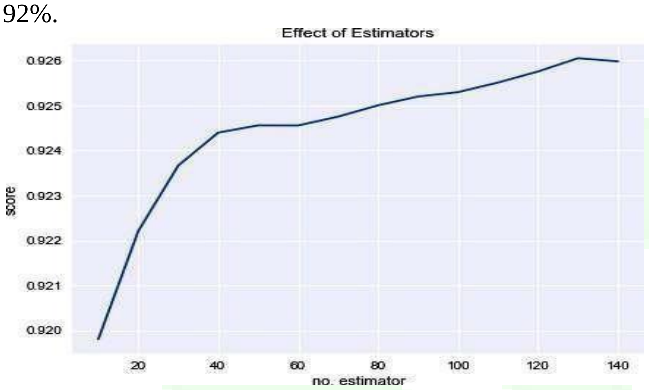

Figure 12: Effect of estimators-2

Figure is 12 is showing effect of the estimators. The number of estimator is 140 then the score is more than 92%.

Table-1Parameters and Values

Sr. No.	Parameter Name	Value
1	Accuracy	95.13%
2	MAE	0.27466%
3	RMSE	0.4478 %
4	R2_Score	0.9213%
5	Classification Error rate	4.87%

Table 1 is showing the simulation results of the KNN Regression technique. The overall accuracy is 95.13% with 4.87% is classification error rate.

Table 2: Simulation Results (Random Forest Regression)

Sr. No.	Parameter Name	Value
1	Accuracy	95.41%
2	MAE	0.2630 %
3	RMSE	0.4398%
4	R2_Score	0.9240%
5	Classification Error rate	4.59%

Table 2 is showing the simulation results of the Random Forest Regression technique. The overall accuracy is 95.41% with 4.59% is classification error rate.

Table 3: Result Comparison

Sr. No.	Parameters	Previous Work [1]	Proposed Work
1	Accuracy	93.8%	95.41%
2	Classification Error	6.2 %	4.59%

VI. Conclusion

The quick rise of sentiment analysis and opinion mining has expanded our data collection interests. We quickly learn what others think of devices and apps we use. Sometimes the numeric rating differs greatly from customer audits. A bound-together evaluation framework is presented to reduce this ambiguity. The final rating combines the featured rating and survey numeric extremity.

Most choose their applications from GooglePlay. Individuals usually choose an app based on its numerical rating. The rating is the average of star ratings from various customers. Clients must also comment. It seems that customer comments and star ratings are inconsistent. It confuses new app users.

This dissertation provides an effective machine learning-based Google Play store mobile app review ranking method. The Python spyder simulation demonstrates that the suggested work has 95.41 % accuracy, compared to 93.8% before. Proposed approach has 4.59 % classification error, whereas previous work has 6.2 %. The simulation findings show that the suggested work outperforms previous efforts.

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