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Call:  08813907089

E-mail ID: ijraset@gmail.com

Ridge regression and the Randomised forest technique are being used to build a classification model in this project. Main objective is to develop a hardware model that can predict overall sales of a latest film based on available resources, playable demos and classifications and production companies and nations. Kaggle has provided us with a sample of 3000 movies (from 1960 to 2017) with all the important facts on everyone one of them (like cast, crew, budget, popularity, date, Genre etc..). It reduces the financial burden on film producers who plan to make a movie.

III. METHODOLOGY

Three stages are included in this operation. Among the three stages are Pre-processing, Modeling, and Testing. Each phase has its own internal procedure. This project explains each step in detail. They're as follows:

A. Pre-processing

In order to develop a model, dataset is an essential part of the process. Data collecting, verification, analysis techniques, and manipulating categorical values are just a few of the phases involved in this process. Model adoption and assessment benefit from increased data quality. This stage consists of the following steps:

B. Data Collection

The collection of data from Kaggle, a cinematic database, provided the data for this dataset, which spans the years 1960 to 2017. It includes details such as the cast, crew, prequel, popularity, budget, and genre of the film. The picture of the database is shown below.

```
data = pd.read_csv("../content/drive/MyDrive/ISRA_project/train.csv")
print(data.shape)
data.head(2)
```

id	belongs_to_collection	budget	genres	homepage	imdb_id	original_language	original_title	overview	popularity
0	1	[{"id": 313276, "name": "Hot Tub Time Machine"}]	1400000	[{"id": 35, "name": "Comedy"}]	NAN	82837294	en	Hot Tub Time Machine 2 When Lou, who has become the father of the it...	6.975383
1	2	[{"id": 107814, "name": "The Princess Diaries"}]	4000000	[{"id": 35, "name": "Comedy"}, {"id": 18, "name": "Romance"}]	NAN	80368933	en	The Princess Diaries 2: Royal Engagement Mia Thermopolis is now a college graduate and ...	8.248895

Fig 1: Dataset of 3000 movies

C. Data Cleaning

We acquired raw data in the form of a dataset. Everything from the cast to the crew to the movie's success to its genre and subgenres are included. Data preparation is a critical stage in the process of transforming raw data into data that can be used to train models. We are deleting all of the dataset's missing value with this step. The following is an example of what I'm talking

```
data_explore.isna().sum()
```

id	0
belongs_to_collection	2396
budget	0
genres	7
homepage	2054
imdb_id	0
original_language	0
original_title	0
overview	8
popularity	0
poster_path	1
production_companies	156
production_countries	55
release_date	0
runtime	2
spoken_languages	20
status	0
tagline	597
title	0
Keywords	276
cast	13
crew	16
revenue	0
dtype: int64	

Fig 3: Checking Null values

Figure 3 displays the dataset set's data type in a separate cell. There are 2034 empty values in the fig-3 main page category.

D. Data Analysis

The third phase in this procedure is dataanalysis. In order to carry out the next stages, it is critical that the data be understood. This stage includes data visualisation. Using a graphical illustration of ordinal data data helps us understand the data better and may lead us to the next step in the process.

Fig-4 shows the top 20 highly interesting films, with the X-axis indicating popularity and the Y-axis indicating the description of the movies. Wonder Women, with a highapproval rating of 294, is the most well-liked film of all time.

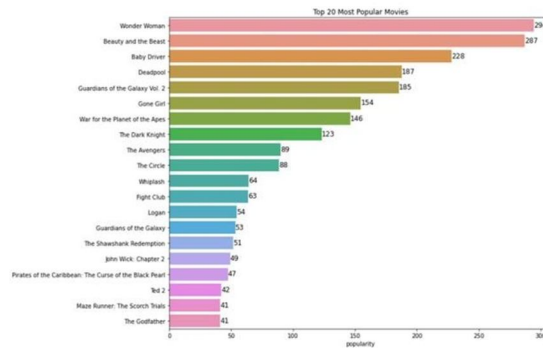


Fig 4: Graphical representation of TOP 20 popularity movies

Fig-5 shows the top 20 highest-grossing pictures, with the X-axis indicating money (as a million dollars) and the Y-axis indicating the name of something like the movies. The Avengers, with a gross of \$1,519 million, is the highest-grossing film.

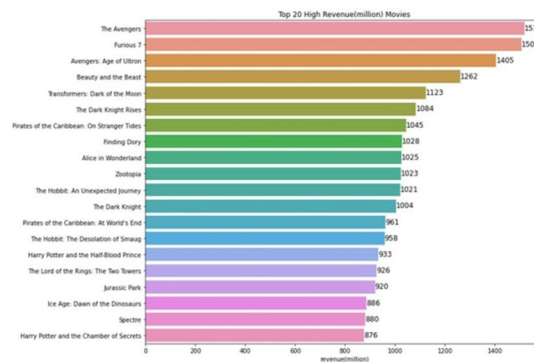


Fig 5: Graphical representation of TOP 20 high revenue movies.

Below is Fig-6, which displays data on the top 20 highest-grossing blockbusters, withprofit (in millions of dollars) plotted on the X-axis and movie titles as seen on the Y- axis. Pirates of something like the Caribbean: On Random person Tides had a budget of 380 million dollars, making it the most expensive film ever made.

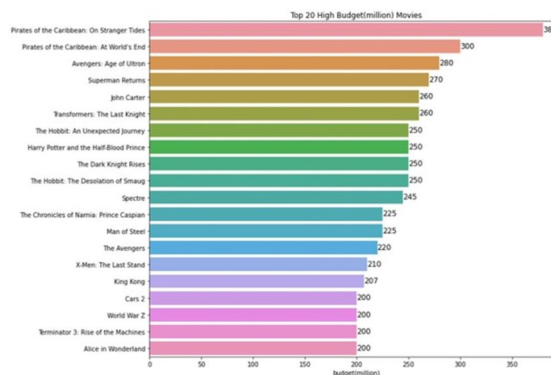


Fig 6: Graphical representation of TOP 20 high budget(million) movies

With budget(in millions) on the X-axis as well as movie title on the Y-axis, Fig. 7 shows the top 20 biggest producing films of all time.

1316 million dollars is the highest grossing film of all time, making it the most profitable film of all time.

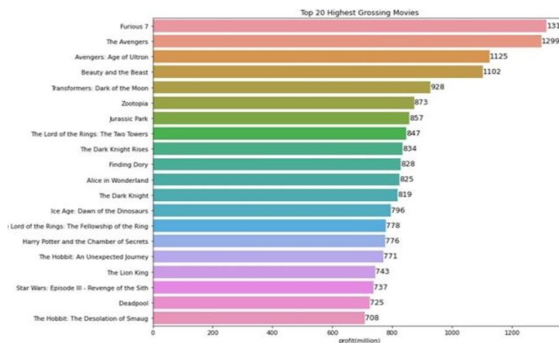


Fig 7: Graphical representation of TOP 20 highest Grossing(million)

The number of films in various genres is depicted in Fig. 8 below. The X-axis shows the various genres, while the Y-axis shows the total number of films in each category. According to the graph below, there have been 1531 films based mostly on genre of drama produced in theatres.

In Fig-9, the link between Musical styles and Mean average Popularity is depicted. The X-axis represents genre kinds, while the Y-axis depicts the level of popularity for each genre.

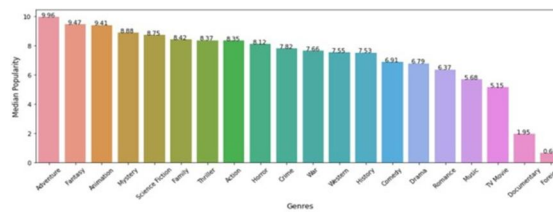


Fig 9: Genres versus Median popularity

Fig-10 shows us the total amount of money spent and the amount of money made for a certain genre. When it comes to the X-Axis we used genres, and the Y-Axis was used to add up the total number of genres (in million).

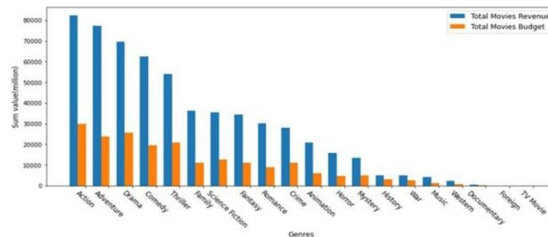


Fig 10: Budget and revenue of particular Genre

Fig. 11 illustrates the revenue-to-budget connection. X-axis was the budget, and Y-axis was the revenue generated by the company.

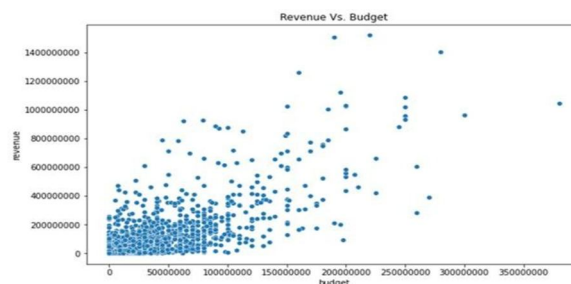


Fig 11: Scatter plot representation of Budget vs Revenue.

The link among both revenue and popularity may be seen in the graph below (Fig. 12). Attraction and profitability were measured on the X-axis and the Y-axis.

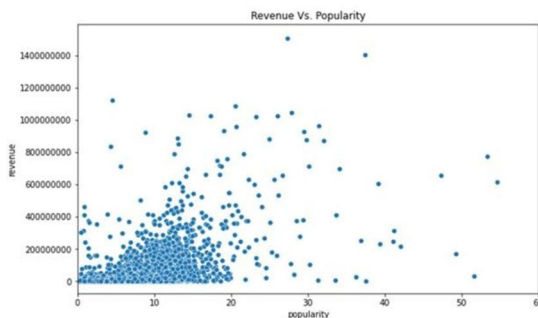


Fig 12: Scatter plot representation of Revenue vs Popularity

Revenue and movie runtime are shown in the following Fig-13. Runtime was plotted on the X-axis, while revenue was plotted on the Y-axis.

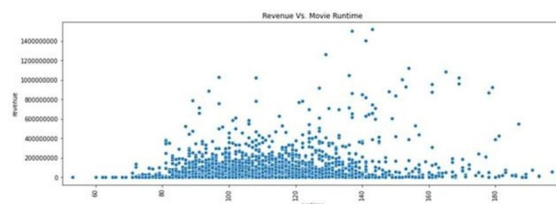


Fig 13: Scatter plot representation of Revenue vs Movie Runtime.

The movie's total revenue for each of its release years is depicted in the graph below.

In the following graph, movie ticket sales for each of the months in which the films were released are shown.

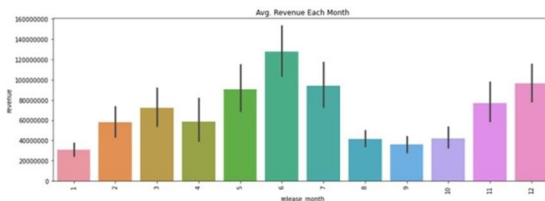


Fig 15: Scatter plot representation of Revenue vs Movie Release month.

An overview of worldwide box office receipts for various languages is shown in the table below.

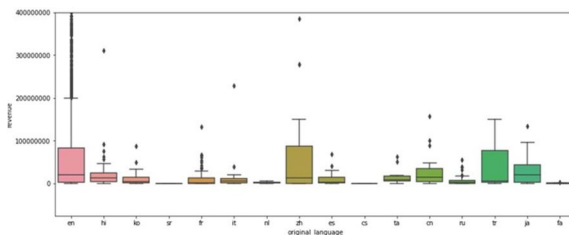


Fig 16: Scatter plot representation of Revenue vs Movie Original language.

We've also figured out how each feature relates to the others, and we expressed that information graphically. There are pleasant and unpleasant correlations between the variables we observed.

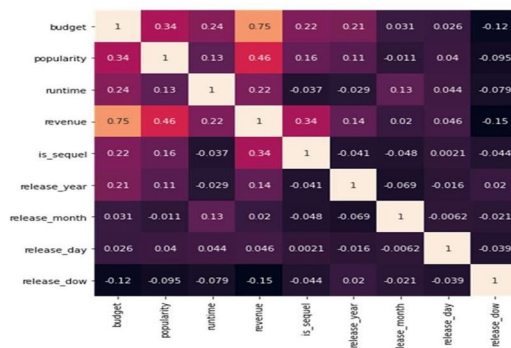


Fig 17: Correlation of each feature of dataset

E. Handling Categorical Values

Attribute data and category values are incompatible with neural network models. So, the categories values must be handled before the model can be implemented. Handles is just like the log - log plot of the values. It aids in the quantitative transformation of attribute variables.



Fig 18: Dataset and datatypes after applying one hot encoding

IV. RESULT AND DISCUSSION

Several films with unknown box office grosses were fed into the model once it had been trained successfully. Even though there were a few null values and similar factors like genres, size, and appeal, his model was able to accurately calculate the gross receipts for all 4000 movies included in the data set. Titles like Pokemon: The Rise of Darkrai, Attack of the 50 Walking Woman, Love, Incedies, and Inside Deep Throat are expected to bring in a lot of money. Output.csv contains a total of 4000 films' estimated revenues, which have not been tied to the profit.

V. CONCLUSION

We can now estimate the model's income more accurately thanks to Big Data in Cinema Analysis, reducing the uncertainty that sometimes accompanies this type of analysis. The primary goal of this research isto study and create a classification model that can forecast the movie's income. We used Kaggle's dataset, which includes information on 3000 films, including information mostly on film's title, cast, and production. Two separate classification methods are used in this project to evaluate, visualise, and train the dataset. Regularization and Randomised Forest are the two methods. Algorithms are evaluated based on their RMSE values, and the one with the lowest score is selected. Last but not least, we've estimated the box office receipts for 4000 pictures in the database that weren't previously associated with their box office receipts.

	title	revenue
0	Pokémon: The Rise of Darkrai	4.312409e+06
1	Attack of the 50 Foot Woman	1.574562e+06
2	Addicted to Love	6.327415e+06
3	Incendies	1.014175e+06
4	Inside Deep Throat	6.030557e+05



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- [2] Sentiment Analysis of Movie Reviews using Machine Learning Techniques. Palak Baid, Apoorva Gupta, Neelam chaplot, 2017.
- [3] Movie Success Prediction using Data Mining. Anantharaman V, Ebin G. Job, Neha sam, Sheryl Maria Sebastian, 2019.



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