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An Aspect based Sentiment Analysis of Tour and Travel Recommendation Approach using Machine Learning

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Abstract: Consumers nowadays are more inclined to depend on internet aspect to help them make educated selections when purchasing products and services. These technologies enable businesses to get insight from the experiences of their consumers and pinpoint areas in which they may enhance the products and services they provide. A survey found that 82 percent of adults in the United States have relied on online reviews when making a purchase. Approximately forty percent of them report that they have told other individuals about the things that they have purchased. Regrettably, it is exceedingly difficult to make accurate predictions about the ratings that new users and goods will get in the recommender systems. The difficulty in question is often known as the cold-start problem. In this article, we will discuss a new method of filtering known as hybrid filtering, which combines collaborative filtering, content-based filtering, and demographic filtering. The hybrid filtering approach that has been presented takes into consideration the numerous demographic particulars of a user in order to forecast the ratings and locate other items in the area that are comparable. This strategy gets beyond the problems that are inherent in more conventional techniques of suggestion, such as CF and CB. After that, the points of interest (POIs) that are pertinent to the user are extracted using the data that were gathered for this article. With the help of the data that was obtained, we were able to carry out a prediction study on the ratings for the various airline services. The findings of this study showed that the most common complaints about business class were related to the quality of the food and the friendliness of the staff, whereas the most common complaints about economy class were related to the level of comfort provided by the seats and the amount of legroom available. In this research, the machine learning (ML)-based hybrid filtering algorithm that was suggested worked quite well. It has the potential to assist in the resolution of the cold-start issue by determining the goods that are most likely to be valuable to the customers.

Keywords*: *Airlines, Cold-start, Customer satisfaction, Hybrid filtering, Personalized recommendation, Text mining, Tourism, Tourist.

1. Introduction

Through online feedback, companies are now able to reach out to their consumers and get input that can be used to enhance customer care. They are now able to interact with their consumers and supply them with the aspect that is necessary for them to make well-informed choices as a result of this new means of communication. Businesses may enhance their customer service by recognising the problems that their customers have with the service via the use of feedback received from their customers [1]. After that, you can instantly put this method into action to fix these problems and provide a satisfying experience for their clients. Businesses stand to benefit enormously from the use of online reviews because of the enhanced marketing possibilities that these evaluations might provide [2].

The good image of a product or service may be observed in online reviews, which can generate a marketing advantage for a firm both in the short term and in the long run. According to a poll that was carried out by the Pew Research Center, 82 percent of people in the United States read reviews or ratings for the very first time before making a purchase [25]. Forty percent of those who participated in the survey provided responses indicating that they did so nearly frequently or always. When asked, over half of those between the ages of 18 and 29 (48%) and those between the ages of 30 and 49 (47%) answered that they almost always or always check internet reviews before making a purchase [3]. The findings of the poll also showed that the age range of individuals who read online reviews is an extremely significant factor when it comes to making a buying decision. The proportion of individuals in this age bracket who make purchases is becoming smaller despite the growing use of online reviews as a purchasing resource [4].

Although the age gap between the users of online reviews is not very large, people under the age of 50 in the United States are more likely to post their own product evaluations than those over the age of 50. Because of the availability of these evaluations, companies have been able to obtain a more in-depth knowledge of the responses of their consumers and enhance the quality of their service [24]. When it comes to making use of online reviews, one of the most significant considerations that companies can make is

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ensuring that their consumers have access to a variety of different options from which to pick. It is exceedingly difficult to manually examine the reviews' data because of the intricacy of the reviews themselves. In this study, we analysed the data with the use of machine learning algorithms, which allowed us to get some insights. We have been able to do a variety of tasks, including normalisation and stemming, as a result of our work with natural language processing [5].

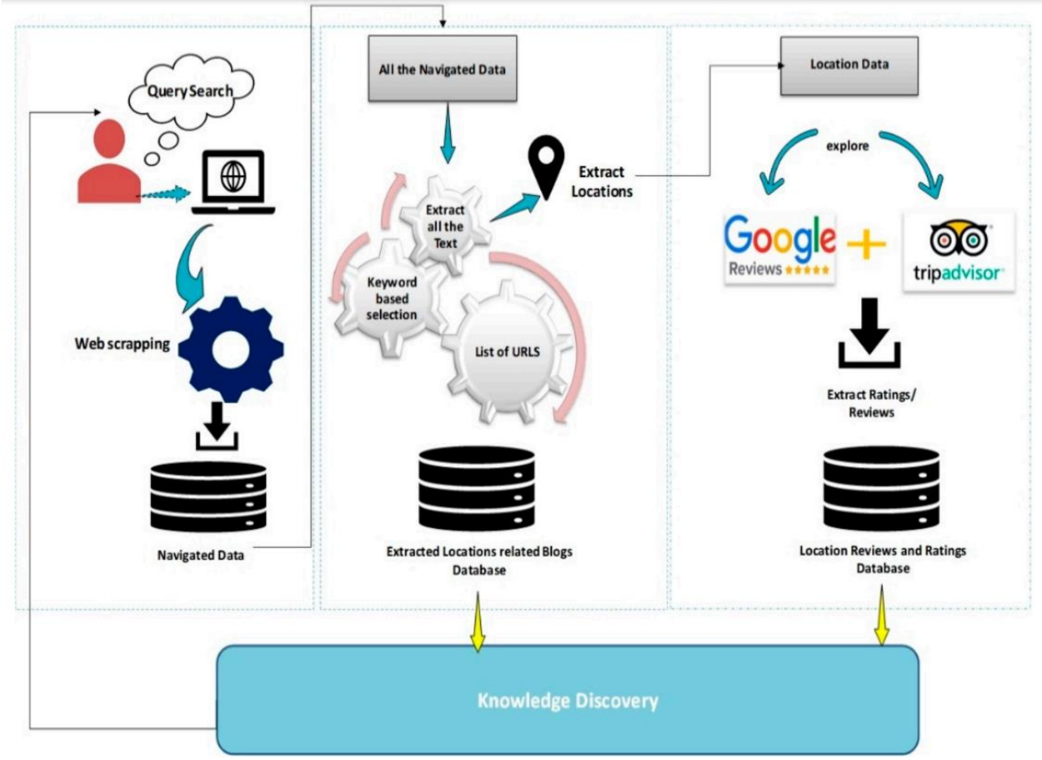


Fig 1: Hybrid Filtering based Sentiment Analysis

Over the course of the last several decades, the tourist sector has played a crucial role in the economic growth of a number of different nations. It has been noted that visitors want to take a break from the demands of their day-to-day life so that they may spend time with their relatives and friends when they are on vacation. When planning a trip, many people think about paying a visit to their loved ones and friends, having a checkup at a doctor's office, and participating in religious activities [6]. These are just few of the reasons people travel. Together with tour operators and individual travellers, the departments of tourism development from a number of different nations are collaborating in order to forge strong connections [23]. The tourism business is home to a wide variety of attractions and facilities that are open to the public for usage. Given the circumstances, it is imperative that the visitor choose a location that offers a variety of activities and attractions to participate [22].

The visitor depends on the aspect that they collect from a variety of sources such as travel agencies, websites specialising in tourism, and travel guides [21]. These sites provide the traveller a vast quantity of aspect that may be used to assist them in organising their trip more effectively [7]. Unfortunately, the sheer volume of available aspect might make it challenging for tourists to organise their itineraries. The absence of individualised suggestions is one of the most often voiced criticisms that travellers have about the websites that are run by the tourism sector. These websites do not provide a customised suggestion; all that is shown is the number of times the traveller has been to the different points of interest [8].A customised suggestion is in more demand than ever before as a result of both the growing number of visitors and the complexity of the aspect that they collect [20]. Because of this, the tourism sector has begun building systems that are intended to make suggestions based on the person's profile. Specifically, these systems will take into account the travel preferences of the individual. PRRS stands for "Personalized Tourist Recommendation Systems," which is the name given to these kinds of systems. The use of PRRS systems has the potential to assist in the improvement of both the quality of the experience that tourists have and the operations of the tourism department. Additionally, it can assist in preventing the tourists from becoming overly enamoured with the numerous attractions [19].

2. Literature Survey

The Net Promoter Score, also known as NPS, is a metric that can be used to evaluate how successful a marketing effort was [9]. Researchers frequently rely on it to determine the aspects of a product's marketability that are most important to its overall success [10]. It is also crucial to provide a pleasant purchasing experience in order to keep a consistent stream of customers. As the level of importance placed on customer happiness continues to rise, an increasing number of researchers are beginning to investigate the ways in which this aspect influences consumers' decisions to make purchases. A large number of satisfied customers can sway a customer's choice to buy a product, especially if those customers have rated the product positively [11].

When it comes to making judgments on the acquisition of goods or services over the internet, a significant number of people are now turning to the use of customer reviews as a primary source of aspect [12]. By evaluating the goods or services provided by other businesses, they may assist their clients in making well-informed judgments and save them time. A favourable review can also assist an online retailer enhance their sales by attracting more prospective buyers and increasing their customer base [18]. A customer's interest in a service or product may also benefit from an increase in the number of favourable evaluations that have been posted about it. This is due to the fact that a greater number of reviews can sway a customer's choice on whether or not to purchase a hotel room or other service. The trustworthiness of the business should be considered when writing an online review because it is one of the most significant aspects to take into account [13].

Word of mouth is one of the most significant things that businesses may take into consideration in order to increase the level of customer satisfaction they provide for their clients [17]. This is due to the fact that it can give them with a more in-depth understanding of the behaviour of their clients. The use of social media is an essential component of any vacation arrangements, and personal recommendations are an effective way to interact with other travellers. The results of a poll that was carried out on the tourist industry indicate that approximately twenty percent of vacationers rely on reviews as a source of aspect when making decisions on the organisation of their trips. On the other hand, just about five percent of travellers really write reviews to talk about their personal adventures [14].

Text data is a type of aspect that is both extremely big and unstructured in nature. Text analysis is a procedure that may extract and investigate this type of aspect. It is possible to gather aspect from a variety of sources, including tweets and emails, by using it. A machine is able to extract data from a substantial amount of text by using text analysis [15]. For the purpose of this investigation, we make use of machine learning models to perform an analysis on text and extract data from it. When it comes to doing an analysis of a piece of text, one of the most significant considerations that can be made is the word importance [16]. The phrase "TF-IDF" refers to a numerical statistic that determines how significant a certain word is to the overall meaning of a document. To determine it, both the frequency with which a given word appears in a given document and the total number of documents that contain that word are taken into account.

The method of analysing and interpreting the written opinion of other people is known as sentiment analysis, and it makes use of machine learning. After that, it is able to get aspect about a particular review depending on the reasons why the review was either favourable or bad.

3. Hybrid Filtering Based Sentiment Analysis (HFSA)

The recommended system is a piece of software that assists consumers in filtering the aspect that they need by supplying them with the service that is both the most relevant and the most customised. Its purpose is to cut down on the volume of aspect that end users need to sort through. By evaluating the behaviour of its users, the recommender system is able to make educated guesses about the interests and preferences of those individuals. After that, we are able to provide customers the most relevant and individualised service possible by using this functionality. Additionally, it might assist them in making well-informed selections about the purchases of items.

The recommender system primarily makes use of hybrid, content-based, and collaborative filtering as its primary methods of operation. In most cases, a user's previous purchases are used to inform their content-based suggestions. The aspect on ratings that was gathered from the different sources is then used by these approaches to develop a tailored suggestion.

This function is often referred to as model-based or item-based filtering amongst industry professionals. It takes into consideration both the similarities and the distinctions between the many items that have been bought in the past. After then, an estimate for the new item is developed using the characteristics of the earlier acquisition. After then, a suggestion is produced by using the similarity measurements that have been made in the past.

In order to discover the similarities that exist between a new and an existing item, a K-Nearest neighbour measure as well as vector space models are used. The KNNs are then used to place a newly discovered object into the most appropriate class possible. The X and Y values of the prior acquisition are used into the calculation used to determine the Euclidian distance that exists between the two items.

$$d(X,Y) = \sqrt{\sum_{i=1}^{n} (ya_i - xa_i)^2} \quad \dots (1)$$

After then, the distance between the two products is calculated by factoring in the X and Y values of the earlier acquisition as part of the calculation. The next step is to provide recommendations for the top n items that meet the criterion value. The ratings aspect that is gathered from several users is used by collaborative filtering algorithms to make predictions on the worth of an item for a particular user. Memory-based or user-based collaborative filtering are typical names for this specific kind of collaborative filtering. It does this by analysing the similarities between the things that a user has bought in the past and making predictions about the new products the user will buy based on those predictions. This technique needs the user's goods or history in order to locate other users who are similar.

$$\mathrm{sim}(u1,u2) = \frac{|s1 \cap s2|}{|s1|+|s2|-|s1 \cap s2|} \dots (2)$$

The Tanimoto coefficient is a well-known instrument that is used in the process of computing the distance that separates two users. It is possible to utilise it to determine the right value for a certain item by taking into consideration the ratings that have been provided by two different users. For example, let us assume that s1 and s2 are two sets of items, each of which contains the ratings that were provided by two different users. s1 and s2 are the sets that result when these two sets are intersected with one another.The collaborative filtering process is unable to make accurate predictions when new users join the system because of this unfortunate limitation. The term "cold-start" has been given to this problem. This is due to the fact that the approach does not have any prior history to review in order to examine the similarities between the two users.Increasing the effectiveness of a system is possible via the use of a strategy known as hybrid filtering, which is a mix of user-based and knowledge-based approaches. The two approaches, each of which has its own set of benefits, may be combined in such a way as to circumvent the shortcomings of the first and second approaches, respectively.Techniques that are based on the user and methods that are based on knowledge often provide benefits that are connected to the efficiency of the system. For instance, the CB technique may perform quite effectively in circumstances in which a user has not rated an item. In a different scenario, the user has already rated an item that has been reviewed in the past by one of the other users.After the results of the CB test have been examined, the user-based procedure known as CF may be used in order to get the suitable items for a particular user. In order to increase the effectiveness of a system, it is possible to combine this technique with the method based on existing aspect. In 2010, Smyth and Cotter proposed a hybrid recommendation system that blends the strengths of user-based and knowledge-based approaches into a single set of functionalities. The consumers may more accurately forecast the ratings and locate goods that are comparable with the aid of this strategy.

Claypool et.al., have provided a hybrid model, which incorporates the capabilities of the user-based approaches as well as the knowledge-based methods. It enables the system to make an educated guess as to which mix of CF and CB will work best for each individual user. Unfortunately, when a new user logs into the system, the hybrid filtering approach is unable to make accurate predictions for related items since it lacks access to the user's prior history.They offered a hybrid technique as a solution to the problem of cold-start, which would combine the strengths of two existing approaches: the user-based method and the knowledge-based method. It enables the system to make accurate predictions about the CF and CB combinations that are best suited for each individual user. This technique, which is also known as demographic filtering, takes into consideration a number of different aspects of the user, such as their age, gender, and country of origin.

A unique hybrid filtering system that combines the capabilities of CF, CB, and DF is proposed in this research study. The three strategies are as follows: Collecting demographic aspect about users at the time of registration enables the platform to be put to use in the provision of a tailored tourist recommender system. After that, these particulars are put to use in order to filter the data in accordance with their needs.By taking into consideration the many different aspects of the user, the cold-start problem may be solved with the help of the demographic filtering that was described in this study. After that, it may be used to the delivery of individualized services to the customers.

Algorithm 1:HFSAbased user Cold-start

Step 1. The aspect that is obtained by using this application determined by the specifics of the demographic profile of the user.

Step 2. In order to get the aspect, the demographic location of the users also taken into consideration.

Step 3. The user's demographic profile is analysed using the data obtained from this programme, which was downloaded by the user.

Step 4. It is possible to determine the user's age, nation, city, and state by using it, in addition to finding out the user's age and country.

Step 5. The user's demographic aspect is broken down according to the city in which they reside.

Step 6. The ranking of the city is as follows: 1 U1 Sydney, 37 Australia, 4.2 U2 Canberra, 45 Australia, 3.2 U3 Hamilton, 21 Australia, 2.7.

Step 7. On the basis of the aspect obtained estimate using Equation (1) and (2) may be provided for the application's typical star rating.

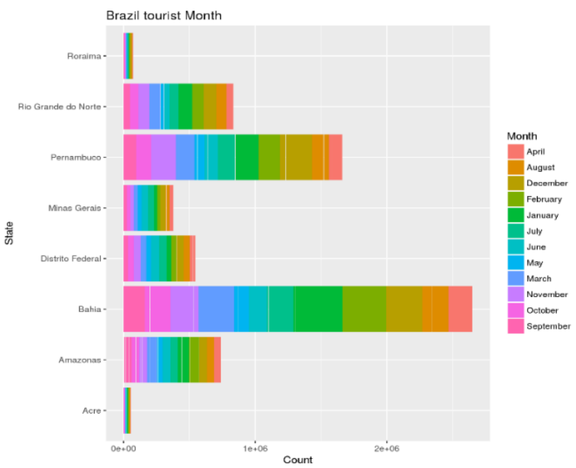
Step 8. After that, it gives the new user a rating and, based on that rating, it makes recommendations on the right travel packages.

The demographic aspect of a new user will be extracted from that user depending on the demographic traits of that user, which is the purpose of this Algorithm -1. We are able to derive aspect about the new user's age, country, city, and gender by using a variety of various combinations of these particulars [26]. Finally, we are able to filter the data according to the name of the tourist package. The table that follows displays an average rating given by a new user depending on the demographic traits that they possess [27]. After that, the rating is affixed to the newly created package vi. The CF technique, which involves first assessing the data, then identifying users in the area who are comparable to the mean [28].

Table 1: Demographic Aspect Rank Details for Package match

S.No	name	city	Package	age	country	rating
1	U1	Sydney	Pkg1	37	Australia	4.2
2	U2	Canberra	Pkg2	45	Australia	3.2
3	U3	Hamilton	Pkg1	21	Australia	2.7
4	U4	Roraima	Pkg1	22	Brazil	3.5
5	U5	Rio	Pkg2	25	Brazil	3.2
6	U6	Bahia	Pkg1	41	Brazil	4.6

Fig 2: A Sample Tourist Visitors in months



4. Experimental Analysis

The purpose of this article is to conduct an analysis of the data obtained from airlinequality.com, which is a database containing aspect on a number of different airline classes. This demonstrates that there are four distinct classes, which are first-class, economy, premium economy, and business class respectively. In the exploratory study, we concentrated our efforts primarily on the economy class since the data from the other classes were much less in comparison to those from the economic class. There are 814 negative reviews and 1186 good reviews on the website, therefore the data gathered by the website is well balanced. People from eighty-five different nations contributed reviews, all of which are written in English. The data is within the acceptable range, and the format of each component has been double-checked to confirm that it is accurate [29].

The process of extracting data from the database is broken down into many parts, which are shown in the form of a data visualisation in Figures 1 through 3. In the exploratory analysis, we made sure that the data were in the appropriate format by taking into account just small English letters and capital letters for each review. The captured text was then tokenized so that we could get the tokens. We combine the many different inflected forms of a single word into a single entry in the database so that we may filter out all of the words that aren't desired there. Lemmatization is the name given to this procedure. The inflected forms on the list are intended to be analysed in order to accomplish the purpose of this strategy, which is to delete them.Python, with the help of the natural language tools, is used to carry out the procedure. After combining all of the different forms of an inflected word into a single item, the next step is to use the n-gram algorithm to determine which phrases are associated with the word. After that, we will use this methodology to do an analysis on the data and get further aspect from it. Building a predictive analytic framework that employs a variety of machine learning approaches to analyse the performance of the models is one of the steps that we take in order to ensure that the users' suggestions are accurate. After that, we strip the review data of any symbols or numbers that were there.After that, we filter the data to eliminate any non-significant stop words. By going through this procedure, the models may be trained, and the outcomes can be evaluated. After the text data have been retrieved, they are put through CountVectorizer's processing, which results in a sparse matrix. After that, we are able to make predictions about the suggestions that will be sent to the customers by using a variety of machine learning models.

In this particular piece of research, we make use of three distinct machine learning models: the decision tree, the KNN, and the SVM. Using the votes cast by our neighbours, we are able to classify objects with the help of this approach. The task of categorization is accomplished by contrasting the numerous characteristics of the thing in question with the characteristics of the group to which it is most closely related. If the item in question has a value of k, then it will be categorised as one of the neighbours that are the closest to it.Finding an ideal hyperplane in a two-dimensional space that correctly classifies a variety of data points is one of the tasks that SVM is designed to assist vector machine learning with. Because each class is located on a distinct side of the axis inside a hyperplane, the hyperplane is able to create the greatest amount of space possible between the various classes.

The DT-A decision tree is a structure that is similar to a flowchart and is made up of nodes that each reflect a test that is performed on an attribute. Each of these nodes stands in for a different class label, and the branch that connects them all illustrates the results of the test.The routes that go from the root to the leaf are a representation of the categorization rules. The purpose of this research is to conduct an investigation into the many aspects that play a part in the choices that travellers make about the airlines they use. Economy class passengers' decisions are heavily impacted by a number of elements, the most significant of which are seen to be the comfort and entertainment offered throughout the journey. However, the duration of the trip and the quality of the flight attendants are also regarded to be crucial aspects that play a role in the decision-making process for business class passengers. On the other hand, things such as aircraft delays and a lack of connection are seen as having a negative impact on the travel experience.

The findings of this research were examined by using not one, not two, but all three of the available machine learning models: KNN, SVM, and the decision tree. When it came to forecasting the suggestions using the data from the review, SVM performed much better than the other strategies.

Data	Algorithm			
	KNN	SVM	Decision Tree	HFSA
Accuracy	64.75	82.75	74.75	83.9
Precision	97.17	85.08	75.4	91.1
Recall	64.24	86.83	82.37	85.2
F1-Socre	77.36	85.94	78.73	88.2

A label was really significant to us in terms of the features that are associated with the classification process, and it helped us perform much better as a result.The findings of the research were studied by making use of KNN, SVM, and the decision tree, which are all various types of machine learning models. KNN fared much better than the other strategies when it came to predicting the suggestions using the data from the review.

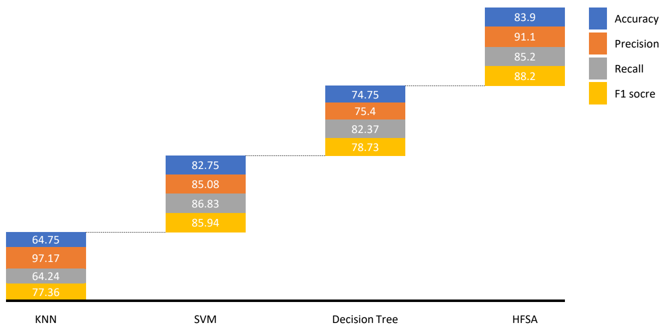


Fig 3: Comparison between classifiers

SVM, on the other hand, fared much better than the other two models in terms of its accuracy. We are also aware that the dataset used for the review comprises a sample, and we make use of it in order to offer an insight of the performance of the review as a whole.

$$\text{Accuracy} = \frac{TP+TN}{TP+FN+FP+TN} \quad \dots (3)$$

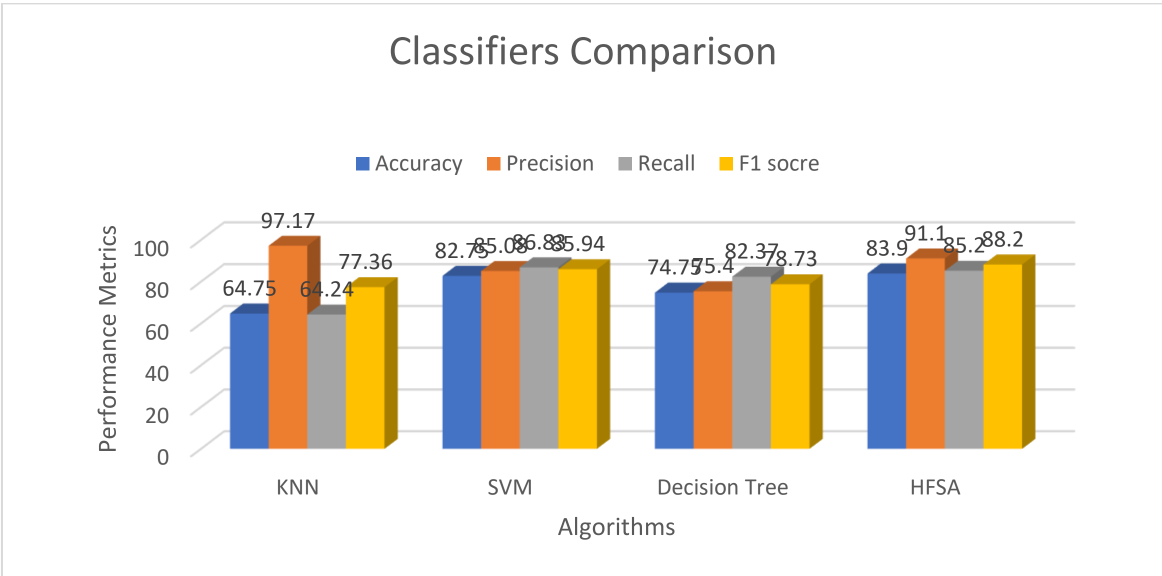


Fig 4: Different Classifiers Comparison

Precision, recall, and the F-measure are the three types of statistical analysis that are performed on the data collected for this research.

$$\text{Precision} = \frac{TP}{TP+FP} \quad \dots (4)$$

The first one, which is used to assess how accurate the categorization process is, is contrasted with the second one, which is used to evaluate how comprehensive the findings.

$$\text{Recall } = \frac{TP}{TP+FN} \ \ldots (5)$$

$$F - \text{ Measure } = 2 * \left(\frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}\right) \ \ldots (5)$$

5. Conclusion

The purpose of HFSAaspect-based work is to conduct an investigation into the myriad of aspects that travellers take into consideration while making their selections on which airlines to use. We were able to determine what elements impact the likes and dislikes of customers travelling in various classes of aircraft thanks to the internet reviews that were gathered and analysed by us.For the purpose of this research, the unstructured text data that was gathered by the airlines was used to conduct an analysis of the numerous aspects that customers take into consideration when making their choice about which airline to fly with. It is therefore possible to utilise it to anticipate the possibility that a customer would suggest an airline, as well as to offer a predictive analysis of how well the firm is doing.The findings of the research showed that ratings are an excellent predictor of the chance that a consumer would suggest an airline, but reviews may also be utilised to make a choice about whether or not to use a certain airline. During the course of the research, we compared the findings of the process of categorization with the findings of the review.As a result of the research, airline companies were able to conduct an in-depth examination of the myriad of aspects that consumers take into consideration while making their selections for air travel. They were then able to utilise the responses produced online to enhance their service limit and forecast the chance of a consumer suggesting an airline. They will be able to acquire feedback more quickly, which will help them improve their performance.Although the research was successful in advancing the usage of online evaluations, it was not able to give a full examination of the different elements that impact the choices that passengers make when it comes to selecting an airline. Because of the terminology that was utilised in the research, the findings might be different depending on the dataset.Textual analysis may be included into the research at some point in the future in order to investigate the myriad of elements that have a role in the choices made by passengers. We would like to express our gratitude to the reviewer for offering insightful remarks and ideas about the research. The experience of this reviewer may contribute to the advancement of the practise of studying internet reviews.

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