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Research Article

Predictive Analysis of Hospitality Industries Global Economic Growth Using Machine Learning Algorithms

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ABSTRACT

In this research study the researcher proposed predictive models on Hospitality Industries to Global Economic Growth. The researcher used the 20 features based on customer personal and professional data and their travel history around the world. The total customer's data 4888 are considered to develop this predictive model. The researcher used the supervised machine learning algorithms to classify the category of customers and Hospitality Industry to Global Economic Growth at world level. The researcher used the accuracy level of predictive model, recall and precision which are given such as Decision Tree Accuracy 0.855974%, Recall-0.891156 , Precision 0.670330, Random Forest Accuracy0.891980%, Recall 1.000000, Precision 0.775076, Ada-Boost Classifier Accuracy 0.845336%, Recall 0.790244, Precision 0.685083, Gradient-Boost Classifier 0.900982%,Recall 1.000000, Precision 0.804805, XG-Boost Accuracy 0.892390%, Recall 1.000000, Precision 0.767647. The researcher found that As far as the model is concerned, 90% accuracy, 72% Recall, and 74% Precision was obtained, which was the best scores out of all the models that were evaluated. While this model may be sufficient to obtain better than chance results for an initial marketing program, it is recommended that a visit to us collect data on Wellness Tourism package sales and customers as the product is being rolled out so that the model can be updated with current data. get better predictions as soon as possible.

Keywords: Hospitality Industry, Tourism, Global Economic Growth, Predictive Models.

INTRODUCTION

Travelers today are increasingly booking their holiday accommodation online. The rise in preference for online bookings has coincided with an increase in the power and persuasiveness of online peer review [1]. The study's key findings reveal that the impact of digital information on sales effectiveness depends on several factors, including the platform used (such as social media or e-commerce websites), the type of product (experience-based or search-based), and the method used to measure sales outcomes. The research offers valuable insights for businesses on enhancing digital marketing strategies by effectively utilizing eWOM and online consumer reviews [2][3]. Customers consider peer reviews to be more independent and trustworthy and tend to rely on them more than information provided by business entities [4][5]. With the rapid growth of online communication platforms and the explosion of two-way information exchange about consumer products and services, online reviews, announcements, opinions and recommendations have become a source of real opportunities and challenges in the tourism and hospitality industry [6] . In other words, consumers find the content of online reviews more useful than recommendations from other online information sources [7]. Online reviews are particularly influential in the tourism and hospitality industry [8].

Sifting through the vast amount of readily available online recommendations and deciding which ones to trust is one of the most challenging tasks for customers when choosing a hotel or restaurant. Customers tend to select a subset

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of reviews to limit the set of possible alternatives. When reading online reviews, customers rate overall rating at 66%, review valence (whether positive or negative) at 63%, review detail at 62%, and reviewer status at 40% as the top four factors to consider [9]. Regarding the valence of evaluations (positive and negative), consumers more easily attribute negative than positive information, according to negative affect theory; thus, negative information can have a stronger influence on purchase decisions [10]. Additionally, online reviews have the ability to garner 30 times more consumer engagement [11].

Because of the connected world, it is easier to voice guest dissatisfaction online than in person. Understanding guest (dis)satisfaction should help one identify the root causes of complaints. This necessitates differentiating customer preferences according to guest classes at the level of particular hotel attributes. When discussing the differences in guest preferences between hotels with higher and lower star ratings [12] According to Liu and colleagues (2017), certain hotels with fewer stars might do better in terms of visitor ratings than those with more stars. Regarding customer complaints, Hu, Zhang, Gao, and Bose (2019) discovered that the primary causes of guest discontent with lower-rated hotels were facilities or cleanliness problems, whereas the primary causes of guest complaints with higher-rated hotels were overpricing and service-related problems. Hoteliers must thus have a thorough understanding of how clients of different hotel classes prioritize various hotel features. Researchers can find significant empirical and useful information by using decision tree (DT) algorithms to the analysis of real data, such as the examination of complaints. In order to better understand online complaint behavior (OCB) and how it varies across visitors to hotels with higher and lower star ratings, this study employs an emerging research style that incorporates user-generated data by examining complaint reviews.

Predicting travelers' online complaint behavior in various hotel industries is another goal of this study. Around $4.5 trillion in consumer spending was generated in 2020 by the global hospitality sector, which includes hotels and other lodging options, as well as eateries, bars, casinos, cruise ships, travel agencies, tour operators, and similar businesses (Hospitality Global Market Report, 2020). In general, the travel and tourism industry contributed $8.9 trillion, or 10.3%, of the world's GDP in 2019 (WTTC, 2020b). The results indicate a short-term emphasis on illness prevention and associated issues, which later lose significance over a longer time horizon, as may be predicted. However, both academics and practitioners are recognizing supply and demand difficulties and technology as important themes in the near and distant future. But generally speaking, where there are notable distinctions between academics and practitioners (such as in the areas of sustainability and branding), practitioners prioritize the more pressing need of financial well-being, whilst academics concentrate on more expansive, long-term trends. [14] Because it creates jobs, boosts foreign exchange profits, and stimulates a number of industries like retail, transportation, and hospitality, tourism is a major driver of economic recovery. [15] varied businesses have varied levels of operational efficiency, and key success factors include labor management, resource allocation, and service quality. Managers in the hospitality sector can benefit from the study's insights on increasing industry competitiveness and productivity. [16] By fostering cultural interchange, drawing in foreign investment, and generating jobs, tourism may work as a sustainable economic engine. But it also draws attention to issues like regulatory frameworks, infrastructural development, and rivalry from other Gulf countries. In order to ensure long-term economic stability in rentier economies, the paper offers policy ideas for utilizing tourism. A study by [17] [18] looks at the connection between economic growth and tourist development in the nations that make up the South Asian Association for Regional Cooperation (SAARC). The study determines if tourism contributes to regional economic growth through panel causality analysis. The results indicate a robust causal relationship between GDP growth and tourism, underscoring the significance of governmental measures to support the industry for economic development. [19] investigates the dynamic relationship between tourism and economic growth in several nations using frequency-domain Granger causality analysis. [20] Examines how tourism contributes to Romania's economic growth. The study examines the connection between GDP growth and tourism revenue using econometric models. [21] [22] According to the research, there is a reciprocal relationship between tourism and economic growth, with tourism development being bolstered by economic growth. These results imply that in order to promote sustainable growth, authorities had to incorporate the rise of tourism into more comprehensive economic plans.

The growth of the hospitality and tourism industry depends on the perception or feelings of the customers. Online reviews or what is called electronic word of mouth (eWOM) provide feedback platforms for hotel customers and potential customers to express their feelings to service providers. These feelings can make or break the growth of hospitality businesses if not managed well. In this article, forecasting analysis was done using hotels.ng as a case

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study. Feature or sentiment extraction was performed using opinion elicitation and data cleaning tools on heterogeneous data sources to assess the decision-making process of hoteliers and tourists. A natural language processing system built using JAVA and a survey questionnaire (Google form) were used to classify the respondents' opinion as positive or negative to verify customer preference. Assessing the quality of experience (QoE) of these customers will help hotels plan or address critical issues raised.

However, in 2020, the industry faced unprecedented challenges and threats due to the COVID-19 pandemic (WTTC, 2020b). Community lockdowns, social distancing requirements, stay-at-home orders, travel and mobility restrictions, and dining restrictions have led to the temporary suspension of many hospitality businesses and significantly reduced demand for businesses that were allowed to continue operating (Bartík et al., 2020, Gursoy and Chi, 2020). While the optimistic scenario predicts a 30% reduction in jobs and GDP compared to 2019, the pessimistic scenario predicts a 60% reduction in jobs and a 62% reduction in GDP compared to 2019 (WTTC, 2020b). Of all industries, global hospitality is among the worst affected, with some markets facing activity reductions of more than 90% (Fernandes, 2020).

The crisis particularly affected the above-average representation of small and medium-sized enterprises in sectors such as accommodation and food services (OECD, 2020). As of June 22, 2020, 513 companies in the restaurant segment filed for bankruptcy (WTTC, 2020c). Large firms also suffered from the decline (WTTC, 2020c). For example, Marriott International, which has 174,000 employees worldwide, has placed tens of thousands of employees on furlough, and Hilton Worldwide announced to creditors in March 2020 that it would take a precautionary $1.75 billion revolving credit facility to preserve cash and maintain flexibility (Nicola et al., 2020).

Numerous scholars have examined the connection between tourism and the continent of Africa's economic development using a variety of approaches and dimensions. Using data from the 1980s to 2005, Akinboade and Braimoh [8] employed a Granger causality test in the early 1920s to verify the connection between foreign tourism and economic growth in Southern Africa. Their results demonstrated a unidirectional causal relationship between international tourism receipts and real GDP. Belloumi [23] provided additional data in the same time frame using the same methodology, demonstrating that tourism had a unidirectionally positive impact on economic growth. Additionally, Ahiawodzi [24] examined the cointegration and causality of tourism revenue and economic growth using the Augmented Dickey-Fuller (ADF) test for unit root, cointegration test, and Granger causality. It discovered a positive association and long-term cointegration between Ghana's tourism industry and economic growth, as well as unidirectional causality.

Similarly, Bouzahzah and El Menyari [25] looked at data from Tunisia and Morocco and found a substantial unidirectional causal association between long-term foreign tourism revenue and economic growth. However, because these studies are limited to one or two nations in the region, academics have not been able to understand the bigger picture as a whole. Using data from Tanzania from 1989 to 2018, Kyara and Rahman's most recent analysis [26] included real GDP, real effective exchange rate, and foreign tourist receipts as variables. Here, a unidirectional causal association between tourism and economic growth was validated by the Granger causality and Wald test results. The Granger causality test is used by the researchers to analyze data from multiple countries in order to determine if tourism drives economic growth or the other way around [27]. Using panel data analysis, the study comes to the conclusion that both factors are significant contributors to long-term economic growth. The study emphasizes that small economies need to invest in education and workforce development in addition to tourism infrastructure in order to maximize economic benefits [28][29].

The study demonstrates that tourism and economic growth are mutually reinforcing through the use of sophisticated econometric methodologies. In order to guarantee long-term advantages, the report offers policy recommendations for governments that strike a balance between promoting tourism and sustainable economic strategy [30]. Payne J.E. and Mervar A. claim that there is a connection between Croatia's tourism industry and economic expansion. Using econometric models, the study shows compelling evidence in favor of the tourism-led growth hypothesis, which holds that increases in tourism have a major role in GDP development. According to the report, Croatia should keep funding marketing and infrastructure for tourists while maintaining sustainability in order to sustain long-term economic growth [31][32][33].

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Numerous studies have examined the connection between tourism and economic growth, with a focus on countries in the Americas. The real GDP to tourism spending elasticity (0.81) indicates that a 100% increase in tourism spending leads to a long-term growth gain of almost 80%. Additionally beneficial is the actual exchange rate, which has an elasticity of 0.35. This was investigated using a Granger causality test as the basis for the study, using data from 1988 to 2009. Despite the fact that tourism is vital to economic expansion, changes in exchange rates may impact revenue from tourism. The research recommends currency rate stabilization policies and diverse tourism strategies to ensure sustained economic benefits [35]. Despite the fact that tourism is vital to economic expansion, changes in exchange rates may impact revenue from tourism. The research recommends exchange rate stabilization policies and diverse tourist strategies to ensure sustained economic benefits [36]. With an emphasis on international studies and empirical analysis, the study shows that tourism contributes significantly to GDP growth and employment creation. The report emphasizes the need for improved marketing, infrastructure, and investment in Ghana's tourism sector in order to boost its contribution to the national economy [37].

OBJECTIVES

This research study is focused on “Predictive Analysis of Hospitality Industry to Global Economic Growth” and its significant research issues. The researcher covered all possible of Hospitality Industry to Global Economic Growth worldwide and formulated the following research issues.

1. To study the global economic growth rate of hospitality Industries.
2. To study the different predictive model on hospitality industry to global economic Growth

To analyze the accuracy level of different predictive model on Hospitality Industry to Global Economic Growth.

METHODS

In this research paper, researchers used Random Forest, Decision tree, XG-boost techniques to control for inconsistent data and provide a higher level of prediction model. Regarding predictive models for machine learning, the researchers used comparative studies of logistic regression and random forest, support vector algorithms, gradient boosting, XG-Boost and light gradient boosting technology to classify customers who are agitated and not agitated in the job market.

Randon Forest Classifiers: Random Forest is a supervised learning algorithm that can be used for classification and reproducibility. It is used in most classification problems. According to scientists, forests are made up of trees, and the more trees there are, the larger the forests become.

Algorithm:

1. Step 1: First start choosing a random sample from the given data.
2. Step 2: Next, the algorithm will build a decision tree for each model and then take predictions from each decision tree.
3. Step 3: In this step, all the predictions will be voted on.
4. Step-4: Finally, select the guess with the most votes as the final guess.

XG-Boost: It is an additional tool developed by many people. XG-Boost uses the Taylor series to estimate the value of the loss function of the training base ft(xi), reducing Emily's burden of calculating the loss for different customers. Input training set $\{ (xi,yi)\}^{n}_{i=1,}$ a different loss function L(y,F(x)), number of iterations M.

Algorithm:

Step-1: Initialize model with a constant value

$$F_0(x)=\arg\min \sum_{k=1}^{n} L(yi, y)......................(1)$$

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Step-2: For m=1 to M

1. Compute so called pseudo residuals

$$r_{im} = \left[\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)} \right]_{F(x)=F_{m-1}(x)} \quad \text{..............(2)}$$

for i=1,2,3,4,..............n.

2. Fit a base learners (e.g tree) hm(x) to pseudo residual i.e train it using the training set $\{(x_i, r_{im})\}_{i=1}^{n}$

3. γ compute multiplier γ_m by solving the one dimension problem

$$\gamma_m = \arg\min \sum_{k=1}^{n} L(yi, Fm - 1(x) + \gamma hm(x)) \text{.....(3)}$$

4. Update the model

$$F_m(x) = Fm - 1(x) + \gamma mhm(x) \text{..........................(4)}$$

Step-3: Output $F_M(x)$

XG-Boost starts with an initial guess and uses the failure to test whether the guess is valid.

In this equation, the first part represents the failure calculating the pseudo-residue and the actual value of the estimated yi value in each leaf where asxi represents the number of features as arguments. Section

Xi=x1,x2,x3,x4.....................xn

Yi=y1,y2,y3,y4,........................yn

Where Xi represents non-uniform data and Yi represents non-uniform data.

5.3 Gradient Boosting

If the tuple (d_i, y_i) represents y_i number of features of a given country on the t^{th} in hospitality Industries, the developed parameterized model minimizes the following objective function:

$$\|e\|_2^2 = \sum_{i=1}^{N} [y_i - \hat{f}(d_i; a, \mu, \sigma)]^2 \qquad (5)$$

Here $\|e\|_2$ represents the standard l_2 norm (i.e. energy of the error) while N is the total number of features under consideration. The parameterized model in equation -1 is defined by the symmetric bell-shaped kernel i.e.

$$\hat{f}(d_i; a, \mu, \sigma) = a e^{-\frac{1}{2}\left(\frac{d_i - \mu}{\sigma}\right)^2}, \forall\, i = 1,2, \ldots N \qquad (6)$$

Where a being the height of the curve while μ and σ represent the central point of symmetry and width of the parameterized model respectively. The model parameters (a, μ, σ) are computed numerically using standard scientific computing library of Python (SciPy), and the results are obtained for each country.

5.4 Decision Tree Classifier

Decision trees use multiple algorithms to decide to split a node into two or more sub-nodes.

$$E(T,X) = \sum_{c \in X} P(c) E(c) \text{.....................(7)}$$

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T=Target Variables whereas X= Features/ Independent Variables

Algorithm:
Step 1: Start the tree with a root node, say S, that contains the complete data set.
Step 2: Find the best attribute in the dataset using Attribute Selection Measure (ASM).
Step 3: Divide S into subsets that contain the possible values for the best attributes.
Step 4: Generate the decision tree node that contains the best attribute.
Step 5: Recursively construct new decision trees using subsets of the dataset created in step -3. Continue this process until you reach a stage where you can no longer classify nodes and call the final node a leaf node.

Nature of the dataset: Source of Data Sets: www.Kaggle.com, Domain: hospitality Industries.

SNO	Column	Non-Null Count	Dtype
1	CustomerID	4888 non-null	int64
2	ProdTaken	4888 non-null	int64
3	Age	4662 non-null	float64
4	TypeofContact	4863 non-null	Object
5	CityTier	4888 non-null	int64
6	DurationOfPitch	4637 non-null	float64
7	Occupation	4888 non-null	Object
8	Gender	4888 non-null	Object
9	NumberOfPersonVisiting	4888 non-null	Object
10	NumberOfFollowups	4843 non-null	float64
11	ProductPitched	4888 non-null	Object
12	PreferredPropertyStar	4862 non-null	float64
13	MaritalStatus	4888 non-null	Object
14	NumberOfTrips	4748 non-null	float64
15	Passport	4888 non-null	int64
16	PitchSatisfactionScore	4888 non-null	int64
17	OwnCar	4888 non-null	int64
18	NumberOfChildrenVisiting	4822 non-null	float64
19	Designation	4888 non-null	Object
20	MonthlyIncome	4655 non-null	float64

Table 1 Dataset description

Total Data Entries: 4888 entries, 0 to 4887
Features/Variables: Data columns:20

The researcher used the data set with 4888 entries where 3910 for training dataset and 978 entries for testing dataset for the efficiency of classifier to classify the data in terms of 70:30 ratio. The entire datasets are represented as follows:

1. Let the complete datasets be represented D= {D1 ,D2, D3, D4.......D4888},
2. Let the training datasets be presented as Train= {D1 ,D2, D3, D4.......D3910},
3. Let the test data be represented as Test= {D3911, D3912, D3913, D314.......D4888},

The splitting of dataset is based on the random manner; system automatically divided the two different datasets in terms of ratio 80:20 manner which is one of the standard mappings to train and test the machine learning model.

RESULTS

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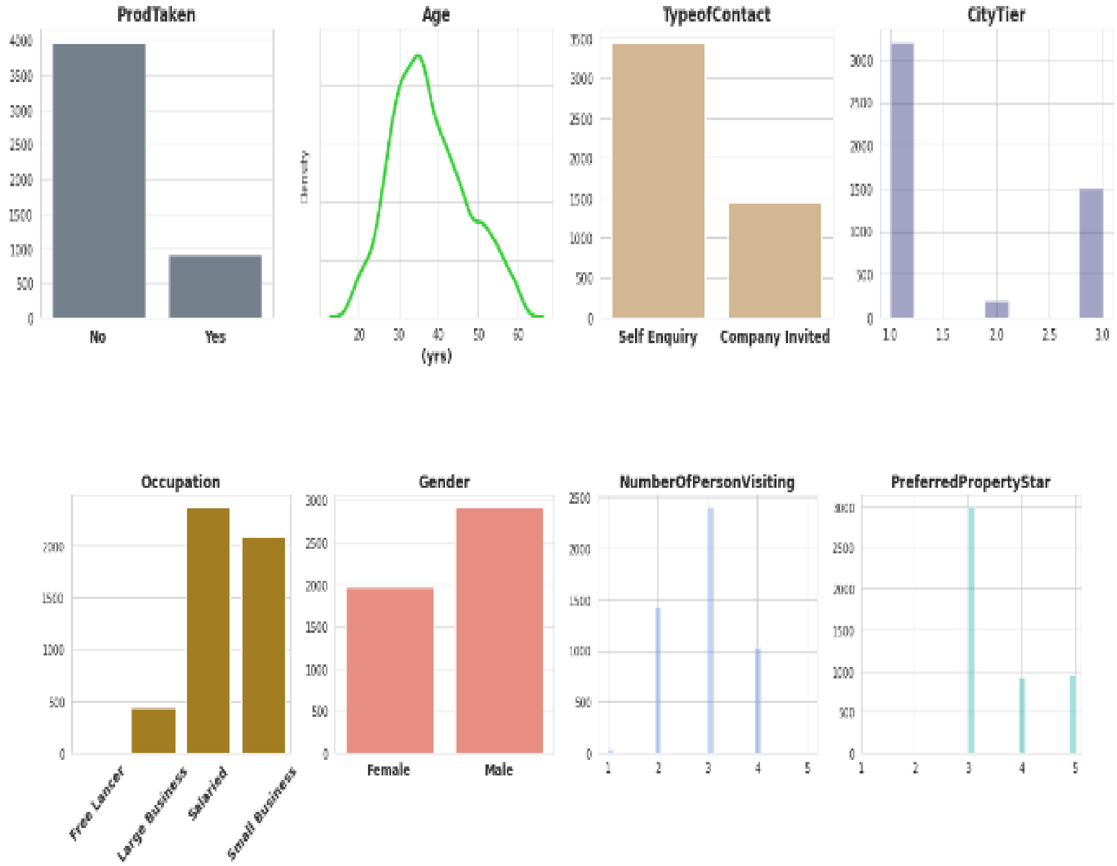

Figure 1 General Statistics of Customers

The above data analysis report is showing the details about the customers such as age group who are more travelling, occupations, gender specification and others features which are using frequently by the customers Figure 1.

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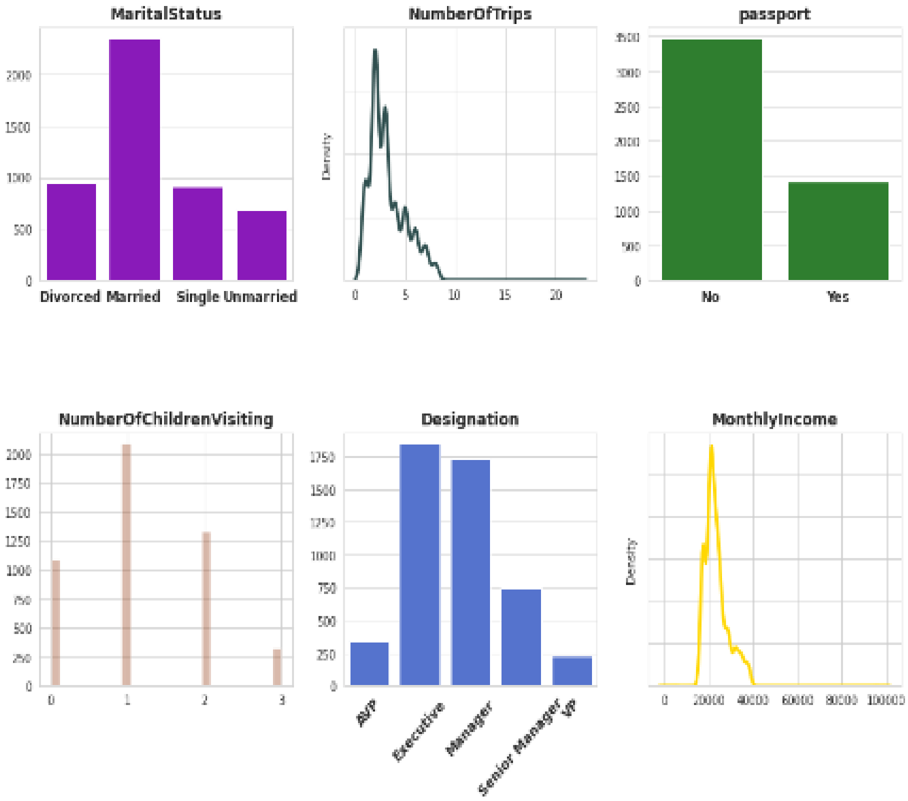

Figure 2 Personal Statistics of Customers

This data statistics showing the family background and current marital status of customers, number of children, number of trips, designations, monthly income, own car or taking rental during the trips, passport belongings, these all factors playing the significant role in hospitality industries with respect to economic growth at global level Figure 2.

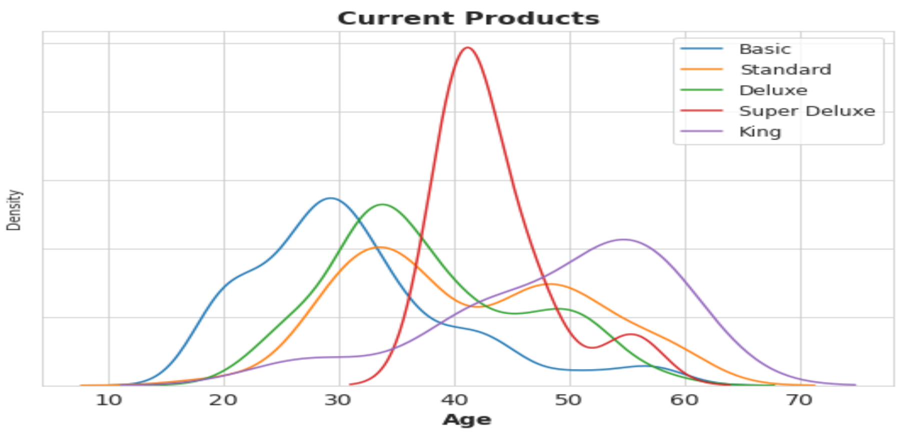

Figure 3: Statistics of Customer Age and Their Hotel Booking

This data statistical analysis report is showing the customer age and categories of hospitality booking standards, during the researcher study the researcher found that age in between 30 to 40 years usually booked the super deluxe level of hospitality (Figure 3). Basic package: popular with customers in their 20s, 30s, and 40s, Standard and Deluxe packages: skewed towards customers in their 30s and 40s, Super Deluxe package: popular with customers in their 40s and 50s, King package: popular with customers in their 40s and 50s.

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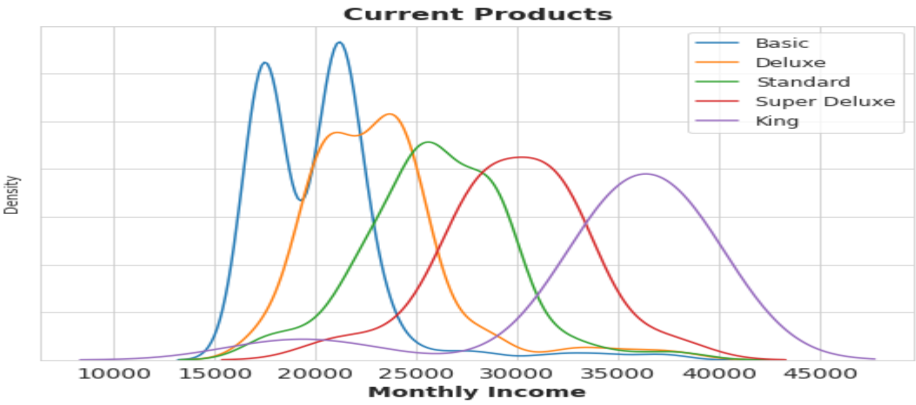

Figure 4: Statistics of Customers Monthly Income and Their Hotel Booking

The above data analysis report is showing that monthly income of customers and their hospitality booking such as Basic Package: Popular with customers with income range between 15k and 25k, Deluxe Package: Popular with customers with income range between 20k and 30k, Standard Package: Popular with customers with income range between 20k and 35k, Super Deluxe Package: Popular with income range between 25k and 35k, King: Popular with customers with income range between 30k and 45k (Figure 4).

S. No	Predictive Models	Accuracy	Recall	Precision
1	Decision Tree	0.855974	0.891156	0.670330
2	Random Forest	0.891980	1.000000	0.775076
3	Ada-Boost Classifier	0.845336	0.790244	0.685083
4	Gradient-Boost Classifier	0.900982	1.000000	0.804805
5	XG-Boost	0.892390	1.000000	0.767647

Table 2. Predictive Analysis

The above data analysis report is showing the predictive analysis of hospitality data and their frequent booking of hotels and trips. There are number of features which playing a significant role in economic growth such as customer age factors, monthly income, number of children, designations, passports, and many others. The researcher used the accuracy level of predictive model, recall and precision which are given such as Decision Tree Accuracy 0.855974%, Recall- 0.891156 , Precision 0.670330, Random Forest Accuracy0.891980%, Recall 1.000000, Precision 0.775076, Ada-Boost Classifier Accuracy 0.845336%, Recall 0.790244, Precision 0.68, Gradient-Boost Classifier 0.900982%,Recall 1.000000, Precision 0.804805, XG-Boost Accuracy 0.89%, Recall 1.000, Precision 0.76 The researcher found that As far as the model is concerned, 90% accuracy, 72% Recall, and 74% Precision was obtained, which was the best scores out of all the models that were evaluated.

DISCUSSION

Finally the researcher concluded that research issues on “Hospitality Industry to Global Economic Growth” has a significant impact with respect to economic growth in the real world. The researcher used 4888 customers data with 20 features which are covered all possible features of customers who are travelling and staying in hotels. The researcher used the different machine learning algorithms and models, the results analysis are showing that except the decision tree and the Ada-boost classifier appear to be slightly overpowered. Ada-boost should not be seriously considered due to its repeated reviews. For the remaining models, the occurrence of over fitting may indicate that the sample weights are compensated by the nature of the algorithms' error correction process. The stacking model is definitely the best performing model here and the predictions from this model will be used up to the exploratory

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analysis of the predicted subset. As for the model, it achieved 90% Accuracy, 72% recall and 74% Precision, which was the best score of all the models evaluated. While this model may be sufficient to obtain better than chance results for an initial marketing program, it is recommended that Visit Us collect data on Wellness Tourism package sales and customers as the product is being rolled out so that the model can be updated with current data which would get better predictions as soon as possible.

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