

## TOURISTS' PERCEPTION AND INFLUENCE FACTORS IN VIRTUAL TOURISM USING BAYESIAN SENTIMENTAL ANALYSIS MODEL IN VIETNAM BASED ON EWOM FOR SUSTAINABLE DEVELOPMENT

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### ABSTRACT

**Objective:** The advancement of Internet technology brought up the tourism industry towards new development and opportunities. With application of the Internet technology tourism industry comprises a vast range of virtual communities such as Trip Advisor, Agoda, Travelocity and so on. Existing research concentrated on evaluating the factors influencing virtual communities' behaviour with limited evaluation of tourist perception. This paper focused on examining the tourists' perception of a virtual tour through the sentimental analysis model based on eWOM for sustainable development.

**Method:** The developed model comprises the group average Bayesian network with the computation of the polarity of the tourist perception. A Bayesian network is a data-driven method involved in estimating dependence among the variable with probabilistic computation.

**Results:** The analysis is based on data collected from sample population in Vietnam with consideration of the 11 variables. Participation intensity, social identity, functional value, emotional value, sharing, interaction, and user satisfaction are among eleven primary variables that have been chosen.

**Conclusions:** The analysis of the results expressed that the user satisfaction level is based on the user's experience and functional value. Additionally, the analysis stated that social value comprises the intermediary role in virtual tourism. This research adds to research methodologies of user engagement methods as well as serves as a reference for theoretical research and management practise in the virtual tourist community.

**Keywords:** virtual tourism, sentimental analysis, bayesian network, tourists perception, functional value, factors, sustainable.

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## PERCEPÇÃO E INFLUÊNCIA TURÍSTICA NO TURISMO VIRTUAL USANDO MODELO DE ANÁLISE SENTIMENTAL BAYESIANA NO VIETNÃ BASEADO NA EWOM PARA O DESENVOLVIMENTO SUSTENTÁVEL

### RESUMO

**Objetivo:** O avanço da tecnologia da Internet levou a indústria do turismo a novos desenvolvimentos e oportunidades. Com a aplicação da tecnologia Internet o turismo indústria compreende uma vasta gama de comunidades virtuais, tais como Trip Advisor, Agoda, Travelocity e assim por diante. A pesquisa existente concentrou-se na avaliação dos fatores que influenciam o comportamento das comunidades virtuais com avaliação limitada da percepção turística. Este artigo concentrou-se em examinar a percepção dos turistas de um tour virtual através do modelo de análise sentimental baseado no eWOM para o desenvolvimento sustentável.

**Método:** O modelo desenvolvido compreende a rede média bayesiana do grupo com a computação da polaridade da percepção turística. Uma rede bayesiana é um método orientado por dados envolvido na estimativa da dependência entre a variável com computação probabilística.

**Resultados:** A análise baseia-se em dados coletados de população amostrada no Vietnã, considerando as 11 variáveis. Intensidade de participação, identidade social, valor funcional, valor emocional, compartilhamento, interação e satisfação do usuário estão entre as onze variáveis primárias que foram escolhidas.

**Conclusões:** A análise dos resultados expressou que o nível de satisfação do usuário é baseado na experiência e no valor funcional do usuário. Além disso, a análise afirmou que o valor social compreende o papel intermediário no turismo virtual. Esta pesquisa contribui para metodologias de pesquisa de métodos de engajamento do usuário, bem como serve como referência para a pesquisa teórica e prática de gestão na comunidade turística virtual.

**Palavras-chave:** turismo virtual, análise sentimental, rede bayesiana, percepção turística, valor funcional, fatores, sustentável.

### 1 INTRODUCTION

Some community groups benefit significantly from the rapid growth of the interactive tourism industry. This industry has recently been regarded as one of the most important contributors to global industry as well as state revenue [Knorr, 2019]. Tourism has become a method sector in Vietnam. It serves as a bridge between diverse development areas. Vietnam, a rich archipelago in Southeast Asia, is demanding more aggressive reactions to tourist establishment, with revenues from innovative imported goods and services as well as job prospects helping respective destinations [Nayoan, et al., 2021]. With rapid development of information as well as technology industry, more tourist research has been performed, with a



particular focus on the use of data as well as technology for promotion as social media and informational media. According to figures given by Vietnam Internet Providers Association, or Asosiasi Penyelenggara Jasa Internet Vietnam (APJII), there were 7.2 Cr Internet users in Vietnam at end of 2016, out of a total population of 9.4 Cr. In September 2016, number of Internet users in Vietnam reached 50.4 percent, with a 33.4 percent increase in number of Facebook subscribers [Li, et al., 2021]. Meanwhile, number of Facebook subscribers had surged by 47.8% by June 2017. According to an Internet world stats survey conducted in 2016, there were only 4 Cr Facebook subscribers [Kwon, et al., 2021].

According to Table 1, social media is the most commonly viewed website [Lai, et al., 2021; Borrajo, et al., 2021]. With 97.4 percent of Internet users accessing social networks or social media, entertainment comes in second, followed by news (96.4 percent), education (93.8 percent), advertisements (93.1 percent), and public services (91.6 percent) [de Almeida, da Costa, de Castro Pires & Pigola, 2022]. According to the APJII survey, 82.6 percent of the community uses Instagram. Meanwhile, 49.6 percent, 90.5 percent, 79.3 percent, and 33.1 percent of Internet users used Path, Chatting/Messenger media, Line, Whatsapp, and BBM, correspondingly [Jain, et al., 2021]. According to the findings, most internet users visit social media daily. The Internet has ushered in a new era of Word of Mouth (WoM) communication, coining the phrase "electronic WoM." (eWOM). Few studies have looked into consumer scepticism in eWOM information uptake [Udin, 2023]. eWOM refers to knowledge exchange via online and public platforms. The image of a tourist site can be shaped both positively and negatively via eWOM [Yusran, 2023]. Evidence suggests that online reviews significantly impact a destination's image [Li, et al., 2022; Kim, et al., 2022].

Table 1: Behavior of Internet Users in Vietnam [Source: Prepared by the authors (2023)]

<b>Types of Content Accessed on Internet</b>	<b>Number of Users (Cr)</b>	<b>Percentage (%)</b>
News	7.9	96.4
Entertainment	8.4	96.8
Social Media	8.2	97.4
Education	7.4	93.8
Public Service	7.1	91.6
Commercial	7.5	93.1



These findings revealed that businesses must reduce eWOM from disgruntled customers while increasing eWOM from highly satisfied customers [Mukhopadhyay, et al., 2022; Singh, et al., 2022].

The contribution of this paper is as follows:

1. To develop perception of the tourists in a virtual tour through the sentimental analysis model based on eWOM
2. The developed model comprises the group average Bayesian network with the computation of the polarity of the tourist perception.
3. The analysis of the results expressed that the user satisfaction level is based on the user's experience and functional value. Additionally, the analysis stated that social value comprises the intermediary role in virtual tourism.

## 2 METHODS

This research provides a sentiment analysis framework for a social network based on deep learning models, including preliminary research, data gathering, preprocessing, modelling and analysis, testing, and assessment. The proposed data collection with extraction process is shown in figure 1. All of the available places to visit are stored in a location database. Our conceptual method extracts all relevant blogs, ratings, and reviews against a user query. Information gathered is both numerical and textual. The system includes a text analysis module that uses context-aware collaborative filtering to accomplish topic modelling and sentiment analysis. The user history-based data analysis method collects demographic information like age, gender, and the number of visitors to a certain place.

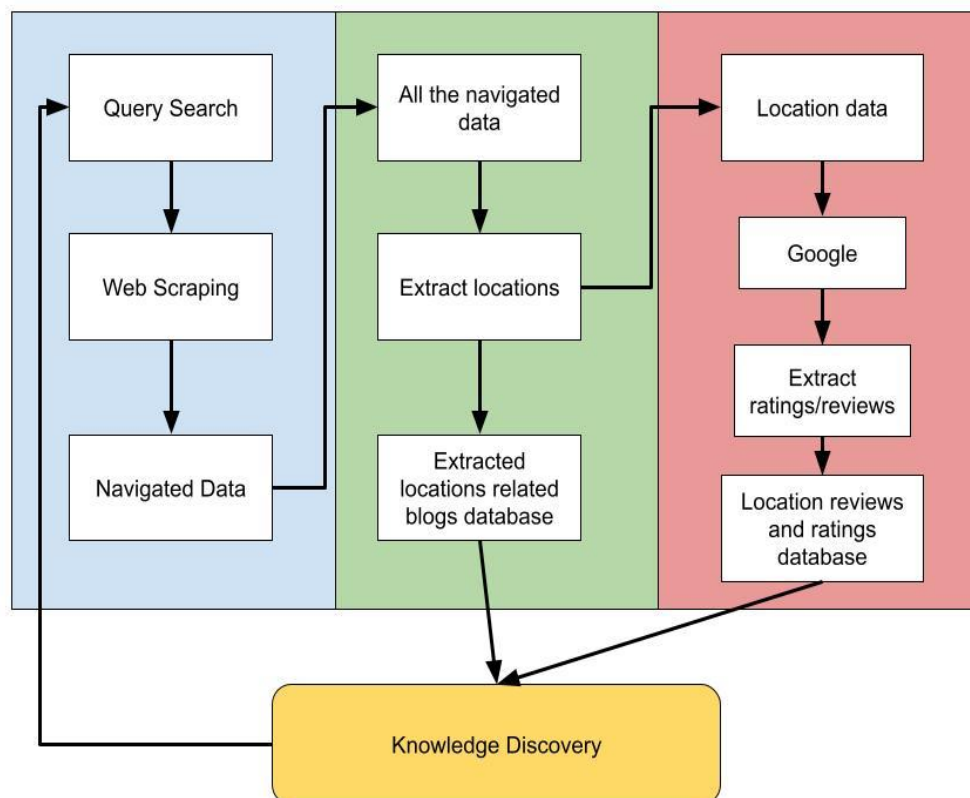
Preferences of a new user are compared to historical data first. Then, a location profile is developed for every site in database for under-emphasized location recommendations, based on historical data, collaborative filtering, and cross-mapping matrices. When a user searches for something, the location database is reviewed first, followed by retrieving all tourist locations, the weather for each place, and the calculation of location profiles based on processing. Customer is then presented with a list of all top locations based on historical data as well as under-appreciated destinations based on location profiles.

The first step is to analyse the text morphologically. It also entails term lemmatization to produce normalised word forms, which is especially significant in languages with several declinations. The text is then divided into fragments based on certain simple principles, such as identifying a noun or noun phrase followed by many complements (adjectives, adverbs, etc.). The goal is to generate a list of fragments that comprise each subject-predicate pair found



in the text simply and appropriately for this type of informal communication. The acquired fragments are then annotated according to their polarity. A polarity annotated lexicon generated in our lab was employed for this purpose. This dictionary contains over 6000 Vietnam terms and was created with a general domain and context in mind. However, using a lexicon alone is insufficient to capture the polarity level of key chunks because semantic interpretation must also be considered.

Figure 1: Data collection and extraction process [Source: Prepared by the authors (2023)]



As a result, some more rules known as "contextual valence shifters" are required [Oh, et al., 2022]. Reversion and polarity augmentation rules were used straightforwardly. The fourth phase is called sentiment categorization, and it involves extracting the sentiment for each component of an object. Our method comprises a simple taxonomy that uses a list of lemmatized and normalised words, each of which belongs to a separate category or topic, to classify fragments by category. A basic string matching is used to assign each word to a category. It's worth noting that each fragment can fit into multiple categories. Finally, each categorised fragment's polarity annotation is counted and aggregated.



## 2.1 GROUP AVERAGE BAYESIAN NETWORK WITH THE COMPUTATION OF THE POLARITY OF THE TOURIST PERCEPTION:

Conjugate priors for the regression coefficients do not exist for classification issues with binary data as well as logistic probability. As a result, mixing in Markov chain Monte Carlo sampler might be poor without the adjusted proposal densities required for implementation of Metropolis–Hastings accept–reject method, as updates are rarely accepted. Model and data are both important in the creation of good proposals. As we will see, introducing the latent variables  $z_i$  simplifies the procedure. The Bayes theorem is used in eq (1),

$$p(\boldsymbol{\beta}, \boldsymbol{\theta}, \mathbf{z}, \sigma^2, \lambda | \mathbf{y}) \propto p(\mathbf{y} | \mathbf{z}, \boldsymbol{\beta}, \boldsymbol{\theta}, \sigma^2, \lambda) p(\boldsymbol{\beta}, \mathbf{z}, \boldsymbol{\theta}, \lambda, \sigma^2) \quad (1)$$

A collection of  $q$  functions of form in eq (2) approximates  $y_i$  in a one hidden layer FFNN method with weight eliminations

$$g_j(\mathbf{x}_i) = \phi_0 \left[ \alpha_{j0} I_{\alpha_{j0}} + \sum_{k=1}^p x_{ik} \alpha_{jk} I_{\alpha_{jk}} + \sum_{l=1}^M \beta_{jl} \phi_h \left( \gamma_{l0} I_{\gamma_{l0}} + \sum_{k=1}^p x_{ik} \gamma_{lk} I_{\gamma_{lk}} \right) \right] \quad (2)$$

Where:

$\alpha_{jk}$  denotes weight on shortcut link from  $k$ th input unit to  $j$ th output unit and  $\alpha_{j0}$  denotes bias of  $j$ th output unit; Weight on connection from  $l$ th hidden unit to  $j$ th output unit is denoted by  $\beta_{jl}$ ; bias of  $l$ th hidden unit is denoted by  $\gamma_{l0}$ .  $\gamma_{lk}$  is an indicator function that indicates efficacy of connection;  $I_z$  specifies weight on connection from  $k$ th input unit to  $l$ th hidden unit;  $\phi_0(\cdot)$  and  $\phi_h(\cdot)$  denote activation functions of hidden units and output units, respectively.  $M$  represents maximum number of hidden units given by users. Sigmoid function, on other hand, will return a constant of 0.5 if input is zero. If we wish to remove hidden unit from network, we'll have to do some extra work to get the constant absorbed by the bias term. The function  $\phi_0(\cdot)$  is set according to the problem at hand. We assign  $\phi_0(z) = 1/(1 + \exp(-z))$  to the sigmoid function. We use the softmax function  $\exp(z_i) / \sum_j \exp(z_j)$  to ensure that the outputs add to one for problems with multiple classes. These settings likewise ensure the probability interpretation of BNN outputs.

The bias terms  $\alpha_{j0}, \gamma_{l0}, \dots, \gamma_{M0}$  will be suppressed in the following by treating them as weights on connections exiting from an additional input unit with a constant input, say  $\mathbf{x}_{t0} \equiv \mathbf{1}$ . Let  $\mathbf{A}$  be vector containing all equation indications (3). The network's structure has three species. Let

$$\boldsymbol{\alpha} = (\alpha_{jk})_{q \times (p+1)}, \boldsymbol{\beta} = (\beta_{jk})_{q \times M}, \boldsymbol{\gamma} = (\gamma_{jk})_{M \times (p+1)}, \quad \text{and}$$



$\theta_{\Lambda} = (\alpha_{\Lambda}, \beta_{\Lambda}, \gamma_{\Lambda})$ , where  $\alpha_{\Lambda}$ ,  $\beta_{\Lambda}$ , and  $\gamma_{\Lambda}$  denote nonzero subsets of  $\alpha$ ,  $\beta$ , and  $\gamma$ . As a result, the tuple specifies the model thoroughly.  $(\Lambda, \theta_{\Lambda})$  We'll refer to the model as  $\theta_{\Lambda}$  only in the following for clarity. We'll also write it as  $g_j(x_i)$  to highlight how  $g_j(x_i)$  is dependent on the model. To perform a Bayesian analysis for method, we must first define it using eq (3)

$$(y|x, \theta_{\Lambda}) \propto \exp \{-\tau H(\theta_{\Lambda})\} \quad (3)$$

Where:

$\tau$  is a tunable parameter, and by eq. (4)

$$H(\theta_{\Lambda}) = \sum_{i=1}^N \sum_{j=1}^q [g_j(x_i, \theta_{\Lambda}) - y_{ij}]^2 \quad (4)$$

This likelihood has not been adjusted. Because it's normalising constant may contain the unknown values, it cannot be utilised directly for Bayesian inference. We'll refer to Neal's classifier as old BNN classifier from here on, and one we presented as new BNN classifier. They are distinct in 3 ways:

The probability function. The likelihood function defined by eq. is assumed by the old BNN classifier (5)

$$f^*(\mathcal{D}|\theta_{\Lambda}) = \prod_{i=1}^N g_1(x_i, \theta_{\Lambda})^{y_i} (1 - g_1(x_i, \theta_{\Lambda}))^{1-y_i} \quad (5)$$

for two-class issues and the likelihood function in eq (6)

$$f^*(\mathcal{D}|\theta_{\Lambda}) = \prod_{i=1}^N \prod_{j=1}^q g_j(x_i, \theta_{\Lambda})^{y_{ij}} \quad (7)$$

Traditional assumptions underpin the term-based model. That is, term-level context can resolve the polarity of the sentiment keyword. Ngrams are common term-level characteristics. We can rewrite Eq. 8 by using  $g_w$  to represent one ngram and  $c$  to represent the context, where  $K$  is the number of features:



$$q_w^* = \underset{q_w \in \{1, -1\}}{\operatorname{argmax}} p(q_w) p(g_w^1, g_w^2, \dots, g_w^K | q_w) \quad (8)$$

We use a training corpus to estimate using maximum likelihood estimation (MLE). The term-based model has two key flaws worth mentioning. First, Eq. 9 shows that all n-grams are employed as characteristics in word polarity disambiguation. Many of them are ineffective. Noise is invariably introduced into the calculation as a result of this. Second, according to Eq. 10, termlevel features are considered independent of one another.

The training corpus should be used to estimate the following parameters:

- $p(t|q_w)$  The likelihood of the opinion target being employed in polarity opinions. The training corpus should include the opinion target t.
- $p(m|q_w)$  The likelihood of the modifying term m being utilised in polarity opinions. In the training corpus, the modifying word m should appear.
- $p(g_I^j|q_w) \{j = 1, \dots, L\}$  The likelihood that the indicative ngram  $g_I^j$  will be employed in polarity opinions. We use the add-one smoothing approach for zero-frequency instances.
- $p(f|c_w)$  The likelihood of the correlative word  $c_w$  appearing in reviews about functions. The training corpus should include the correlative word  $c_w$ .

The data for constructing the model was obtained through literature study and the questionnaire responses from tourism establishments located in Free State. Analysis of obtained data indicated a total of six variables as influencing tourism grading. A Bayesian network model is graphic. Therefore, the model was constructed using Microsoft Word tool. Round shapes were used to depict each variable, while arrows were used to indicate the relationships among the variables. The relationship among the variables was tested using two Bayesian network statistics, namely prior marginals and posterior marginals. The results further show that variables Computer Literacy (CL) and Trained (T) have a direct influence on whether a grading applicant will determine grading application process easy or difficult (Grading Complexity). Additionally, first-level variable Government Funding (GF) has a direct influence on the satisfactory level of grading benefits (Benefits) and affordability of grading cost (Grading Cost). Finally, results indicate that three variables are most significant variables for increasing number of graded tourism establishments.

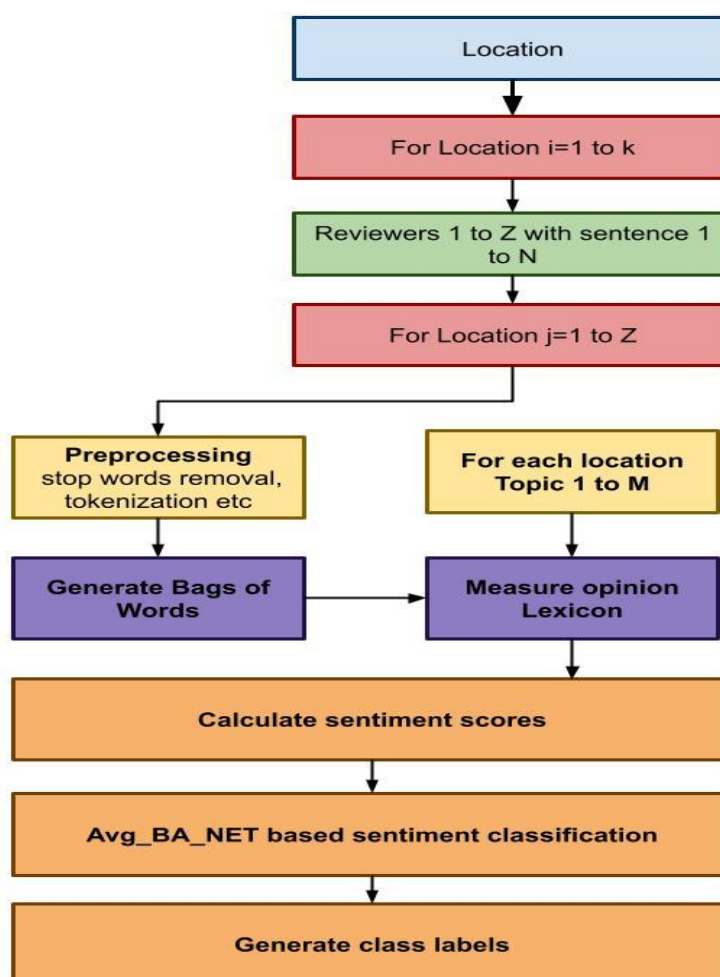




## 2.2 SENTIMENT ANALYSIS

There are several evaluations available for any single tourist attraction on the Internet. We gathered information from two of the most popular review sites, TripAdvisor as well as Google Recommendations. Both of these review sites include ratings and reviews for each location. Platforms' motivation is to screen content based on user ratings. Food, entertainment, cleanliness, fee, and value are all reviews on both sites. Figure 2 depicts a basic approach for sentiment classification using ML methods. As input, we have a range of places from 1 to K. Only reviews from both sites are examined for this phase, and the location ratings are maintained separately. The reviews from both sources are combined for each location, yielding many Z reviews. Every review is broken down into N sentences. Preprocessing is now done for each review, and bags of words are generated. Opinion lexicons are evaluated after preprocessing. Following are main tasks involved in total procedure.

Figure 2: Avg\_BA-NET based sentiment classification flow chart [Source: Prepared by the authors (2023)]





### 3 RESULTS

Python Keros is used to implement our system. In addition, binary-cross entropy based loss function, as well as RMS prop optimizer, are utilized in our model. Throughout 120 cycles, we tested classification models on testing sets.

**Data:** Our data was obtained from Agoda1, an online hotel booking service. We gathered Vietnamese reviews for 50 hotels in Vietnam. Following that, we performed some pre-processing techniques such as phrase detection 2, word segmentation 3, and part-of-speech tagging 4. We also deleted sentences that were not standard Vietnamese, such as those that lacked tone markings. To assess the models' performance, we employed 8 evaluation metrics: error rate, FPR, FNR, accuracy, precision, recall, specificity, and F1 score. The misclassification rate illustrates the sum of false positive and false negative values divided by the total number of erroneous values, as illustrated in eq (9).

$$\text{Error Rate} = \frac{FP+FN}{\text{Total}} \quad (9)$$

Probability of a false alarm is measured by FPR also known as fall-out.

Table 2: Comparative analysis of Virtual tourism in Vietnam [Source: Prepared by the authors (2023)]

Parameters	ISP	TPD	Avg.Ba_Net
Error Rate	63	61	55
False positive Rate	54	53	50
False negative Rate	49	48.5	35
Accuracy	91	94	97
Precision	93	93.8	94
Recall	88.5	88.9	90
Specificity	88	90.5	92
F-Measure	85	86	87



Figure 3: Comparison of Error rate [Source: Prepared by the authors (2023)]

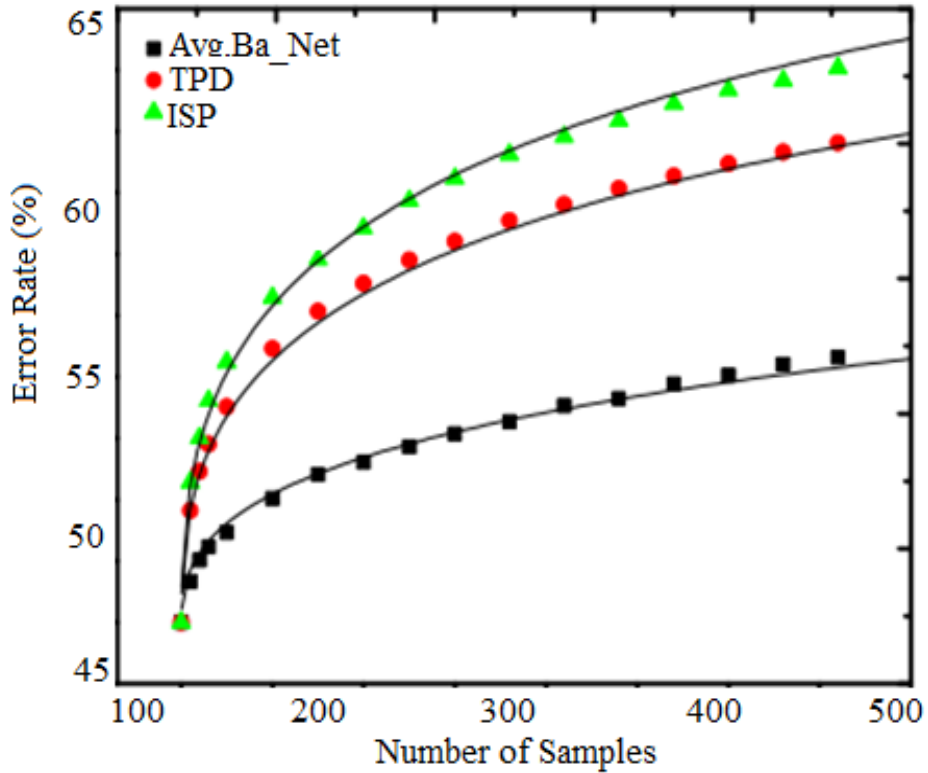


Figure 4: Comparison of FPR [Source: Prepared by the authors (2023)]

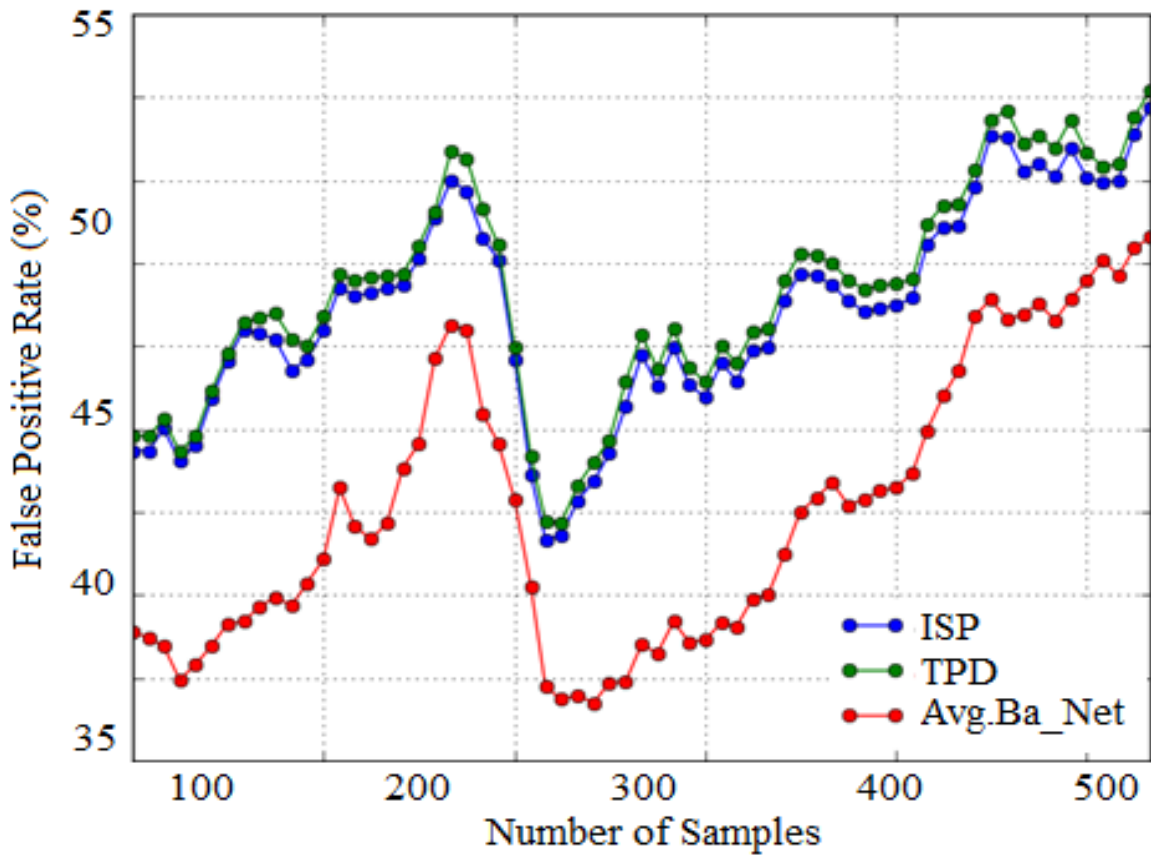




Figure 5: Comparison of FNR [Source: Prepared by the authors (2023)]

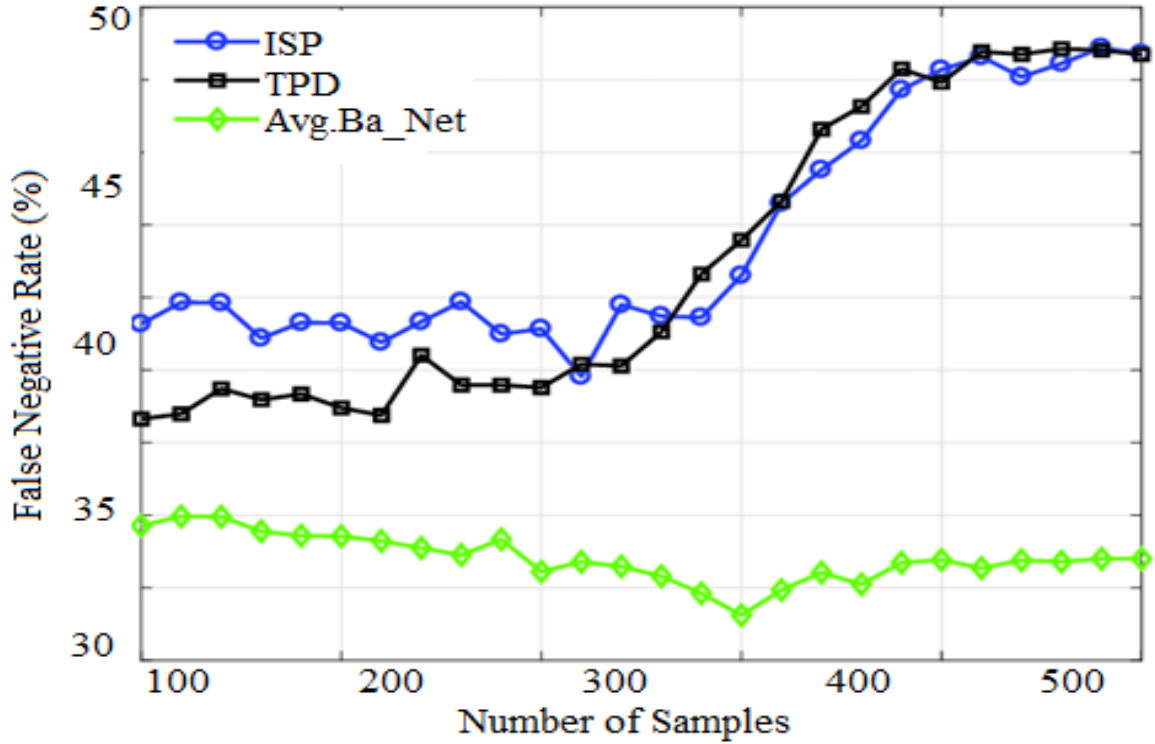


Figure 6: Comparison of Accuracy [Source: Prepared by the authors (2023)]

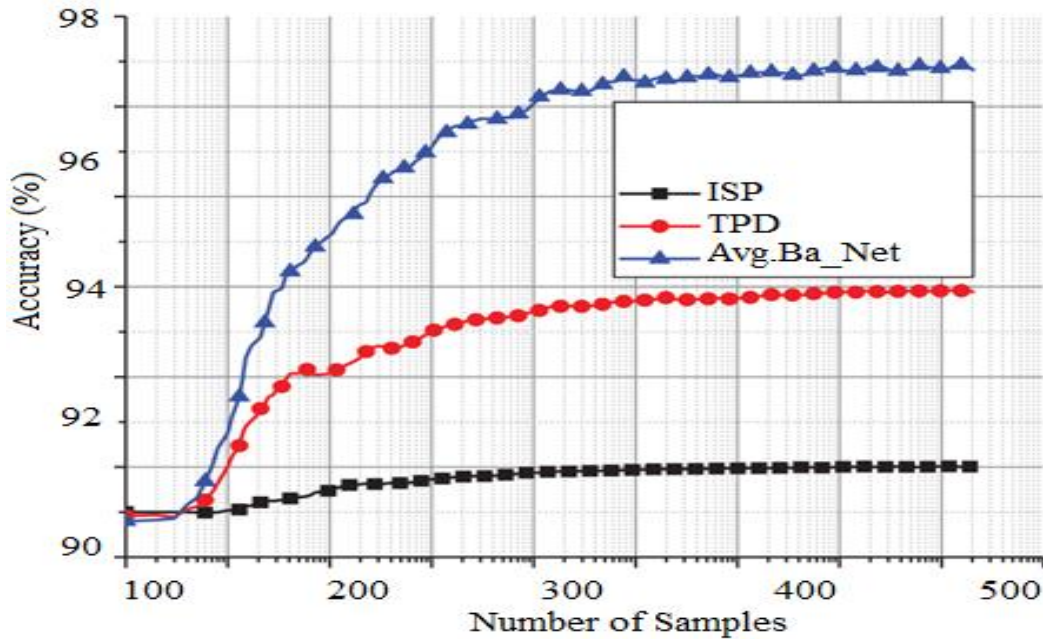




Figure 7: Comparison of Precision [Source: Prepared by the authors (2023)]

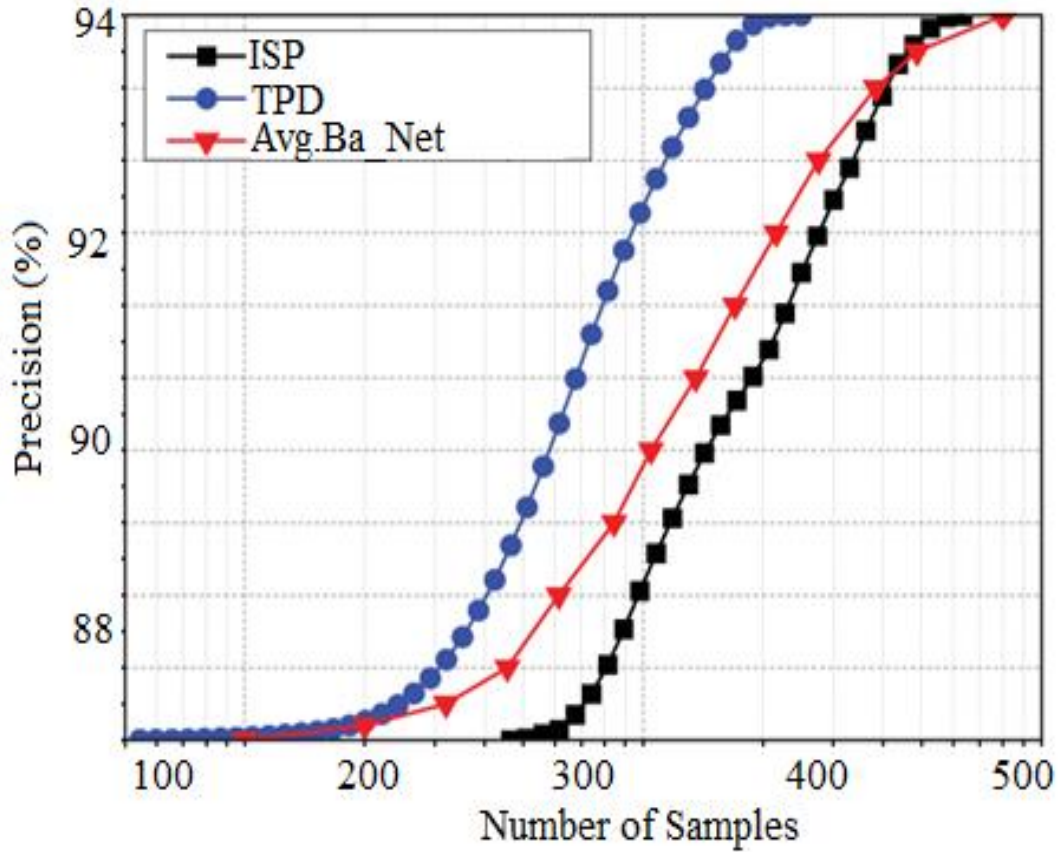


Figure 8: Comparison of Recall [Source: Prepared by the authors (2023)]

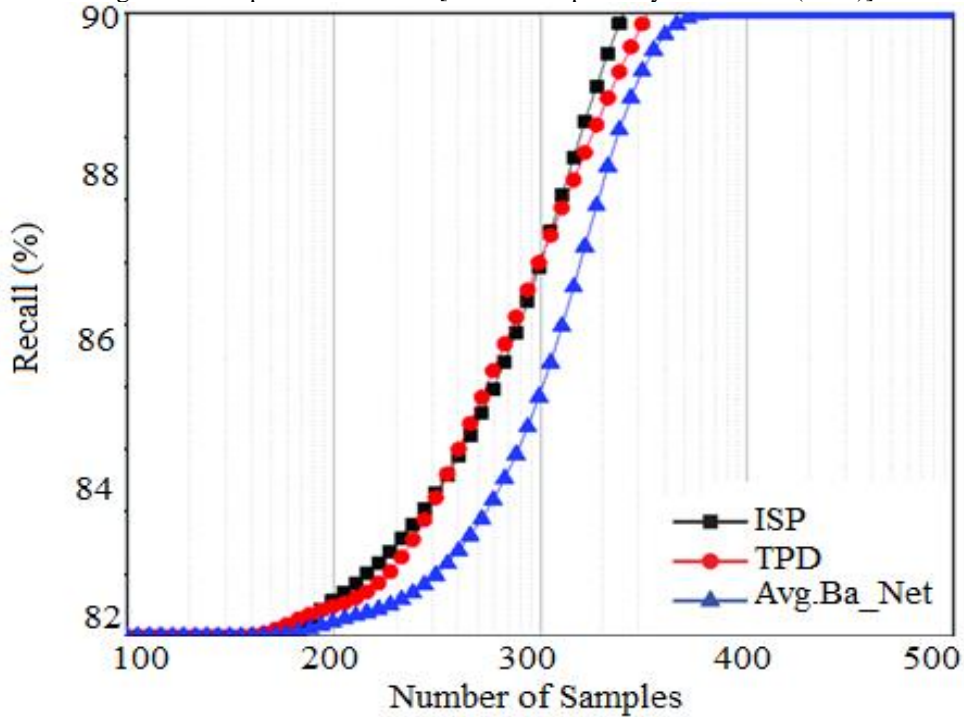




Figure 9: Comparison of Specificity [Source: Prepared by the authors (2023)]

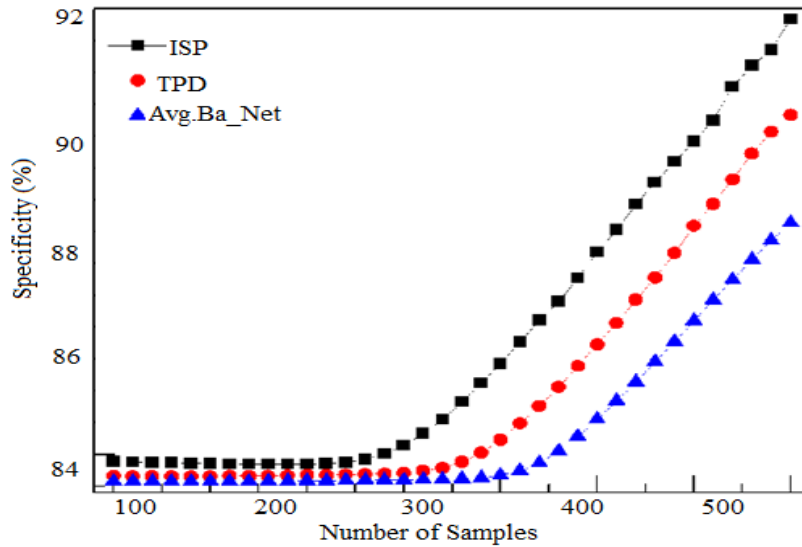
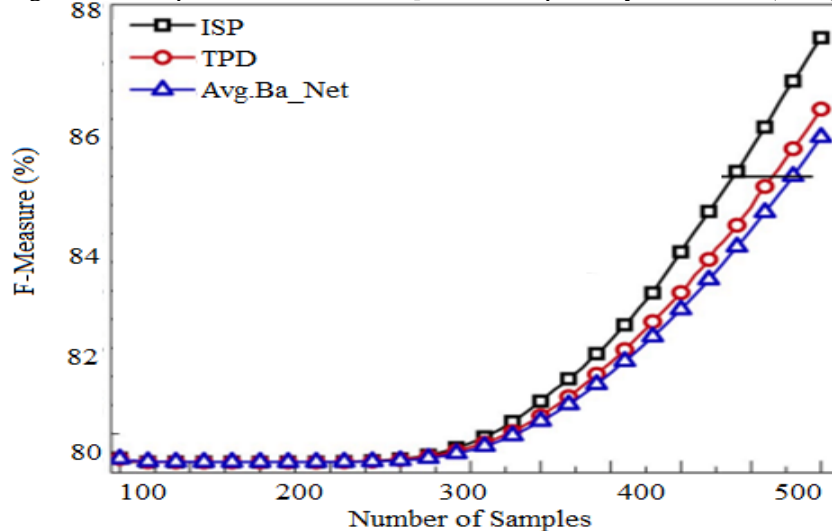


Figure 10: Comparison of F-Measure [Source: Prepared by the authors (2023)]



#### 4 DISCUSSION

The above table 2 shown comparative analysis of Virtual tourism in Vietnam for Agoda1, a website for booking hotels online reviews in sentimental analysis. Here the parameters compared are error rate, false positive rate, false negative rate, accuracy, precision, recall, specificity and F1 score. The existing technique compared are ISP and TDP with proposed Avg\_Ba\_NET. Error rate obtained by proposed Avg\_Ba\_NET is 55%; existing ISP attained 63% and TDP obtained 61% as shown in figure 3. False positive rate attained by proposed Avg\_Ba\_NET is 50%, ISP obtained 54% and 53% by TDP given by figure 4. False Negative rate attained by proposed Avg\_Ba\_NET is 35%, ISP obtained 49% and 48.5 by TDP shown by figure 5. proposed Avg\_Ba\_NET obtained accuracy of 97%, ISP attained 91%, TDP obtained 94% as shown in figure 6. Precision of proposed Avg\_Ba\_NET attained 94%, ISP



obtained is 93% and 93.8% by TDP given by figure 7. Specificity of proposed Avg\_Ba\_NET is 92%, 88% by ISP and TDP attained 90.5% as shown in figure 8. Recall attained by proposed Avg\_Ba\_NET is 90%, ISP attained recall of 88.5%, TDP obtained 88.9% as shown in figure 9. F-1 score obtained by proposed Avg\_Ba\_NET 87%, ISP achieved 85%, TDP attained 86% given by figure 10. From the above analysis the proposed technique attained optimal results in sentimental analysis of Vietnam based tourism reviews using deep learning techniques.

## 5 CONCLUSION

This research proposed examining the tourists' perception in a virtual tour through the sentimental analysis model based on eWOM. The developed model comprises the group average Bayesian network with the computation of the polarity of the tourist perception. A Bayesian network is a data-driven model involved in estimating dependence among the variable with probabilistic computation. The analysis is based on data collected from sample population in Vietnam with consideration of the 11 variables. Participation intensity, subjective norm, group norm, emotional value, social value, interaction and user satisfaction are among eleven primary variables that have been chosen. The analysis of the results expressed that the user satisfaction level is based on the experience of the user and functional value. Additionally, the analysis stated that social value comprises the intermediary role in virtual tourism. This research adds to research methodologies of user engagement methods as well as serves as a reference for theoretical research and management practise in the virtual tourist community. The parametric analysis is given in terms of error rate of 55%, false positive rate of 50%, false negative rate of 35%, accuracy of 97%, precision of 94%, recall of 90%, specificity of 92% and F1 score of 87%.



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