International Journal For Advanced Research In Science & Technology
A peer reviewed international journal www.ijarst.in
ISSN: 2457-0362

Analyzing the Impact of Novelty Seeking in Tourism Choices through Online Travel Reviews

1 Dudekula Shakeel Basha, University College of Engineering, Science and Technology, JNTUH Hyderabad

2 Dr. M Dhanalakshmi, Professor of IT, University College of Engineering, Science and Technology, JNTUH Hyderabad

Abstract: The primary goal of the project is to develop a classification framework and a deep learning model, specifically BERT-BiGRU, capable of automatically detecting the personality trait of novelty seeking (NS) from online travel reviews. Manual classification of these reviews is challenging due to their high volume and unstructured nature. This limitation underscores the need for automated methods to efficiently process and analyze the extensive content. The proposed deep learning model, BERT-BiGRU, based on Bidirectional Encoder Representations from Transformers, has demonstrated success in achieving high precision and F1 scores when recognizing the NS personality trait from the reviews. This underscores the effectiveness of the chosen model. The project establishes that personality traits, specifically novelty seeking in this case, can be automatically identified from travel reviews using advanced computational techniques. This automation offers a more efficient and scalable approach compared to manual methods. The findings of the project contribute by providing a comprehensive classification framework for the NS personality trait. This framework has practical applications in marketing and recommendation systems within the tourism industry, offering valuable insights into customer preferences. The project's broader contribution extends to the development of computational techniques in both psychology and marketing. By applying deep learning models like BERT-BiGRU to identify personality traits from unstructured text data, it advances the use of sophisticated techniques in diverse fields, showcasing the potential of these models beyond traditional applications. The project's extensions include a hybrid model named “BERT CNN-BI-GRU” and “BERT-LSTM-GRU” in which BERT-LSTM- GRU got 99% accuracy.

***Index terms** - Tourism industry, BERT- BiGRU, novelty seeking, online travel reviews.*

1. INTRODUCTION

With the rapid development of information technology, the internet has gradually penetrated many areas of our daily lives. The tourism industry has gradually extended from offline to online. With the emergence of online travel communities, a rapidly increasing number of tourists search the internet for destination introductions and comments about travel experiences from other travelers before making travel decisions [1].

Most online tourism platform reviews reflect what tourists see, feel, and think. Suppose this information is collected and analyzed to visually reveal tourists' praise and criticism attitudes or emotional tendencies about the elements of tourism services. In that case, it will help tourists understand the emotional tendencies of the forerunners towards a certain tourist destination and support tourists in their decision-making [2]. Tour operators can understand tourists' opinions or their attitudes of praise and criticism to maximize their strengths and avoid weaknesses. Reviews also help managers customize products or improve programs and gain a competitive advantage [3].

Personality traits are a group of psychological structures that trigger individual behavior and make individuals respond in the same way to different kinds of stimuli [4]. Traditionally, researchers use self-reporting scales to collect data on personality traits, which requires subjects to self-evaluate their the personality trait measurement scale mainly relies on the subjects' subjective feelings and self-statement, most personality trait measurement scales are currently standardized tests [6]. However, individuals responding to surveys are prone to expressing themselves more in line with social values and more conducive to self-representation. In other words, participants can deliberately submit distorted responses, which negatively affects the efficacy of measurement results [7].

Compared with the measurement of personality traits by psychological tests, personality trait recognition based on online behavior data is a method to automatically recognize and judge personality trait types [8]. On the one hand, it overcomes the subjective and static nature of traditional personality trait measurement methods. On the other hand, it also avoids the measurement bias caused by self-reporting and provides new methods and ideas for tourists' personality traits acquisition.

Novelty seeking (NS) is a personality trait [9], manifested as a general tendency to pursue diversification, curiosity, complexity, and strong feelings and experiences. NS is known to be an important motive for pleasure tourism and is considered an inherent quality [10], [11]. It has been proven to play an inseparable role in the choice of destination and has been one of the greatest impact factors on tourists' perceptions [12]. Previous research has shown that NS affects tourists' return intention [13], destination loyalty [14], and satisfaction [15]. NS is a personality trait widely recognized as an influencer of tourism motivation and plays a crucial role in formulating marketing strategies for the tourism industry. Since NS people like to go to remote and unfamiliar places, in the field of personalized recommendation, new tourist destinations can be recommended according to customers' NS tendencies. In addition to developing better recommender systems, organizations can also design more targeted marketing campaigns based on customer needs. It may help improve tourist satisfaction, reduce information duplication and diversify recommendations.

2. LITERATURE SURVEY

Previous research has confirmed that social loafing as a pronouncing obstacle undermines the development of online communities. However, relevant studies

International Journal For Advanced Research In Science & Technology
A peer reviewed international journal www.ijarst.in
IJARST
ISSN: 2457-0362

centered on the critical factors that affect social loafing in online travel communities are still not well understood. Drawing on self-determination theory and social identity theory, this paper critically focuses on the effects of intrinsic motivation (enjoyment in helping and hedonic motivation), extrinsic motivation (reputation and reciprocity) and community identification on social loafing in online travel communities, using data collected from 300 respondents in China [1]. After a structural equation modeling analysis, the results of this study indicate that only enjoyment in helping exhibits a significantly negative relationship with social loafing, whereas the other three types of motivation are reinforced by community identification to inhibit social loafing indirectly. Meanwhile, community identification is more positively influenced by extrinsic motivation (reputation and reciprocity), and social loafing can be effectively diminished by community identification. Theoretical and practical suggestions are discussed for future research.

On the basis of the self-determination theory, we develop and test an integrative framework that explains when and why customer incivility impairs employee service performance [5]. Using multisource data collected through two waves in a shopping mall, we found that the strength of the mediated relationship between customer incivility and employee service performance (via employee intrinsic motivation) varied based on employee core-self evaluations; the negative indirect effect of customer incivility via intrinsic motivation on service performance was weaker for employees with high levels of core-self evaluations than for employees with low levels of core-self evaluations.

The present study reviews the literature of psychological studies [4, 5, 6, 7, 8] investigating conspiracy beliefs. Additionally, the association between Big Five personality factors and conspiracy beliefs is analyzed meta-analytically using random-effects models. Ninety-six studies were identified for the systematic review [6]. A comprehensive account of predictors, consequences, operationalization, questionnaires, and most prominent conspiracy theories is presented. For meta-analysis, 74 effect sizes from 13 studies were extracted. The psychological literature on predictors of conspiracy beliefs can be divided in approaches either with a pathological (e.g., paranoia) or socio-political focus (e.g., perceived powerlessness). Generally, there is a lack of theoretical frameworks in this young area of research. Meta-analysis revealed that agreeableness, openness to experience, and the remaining Big Five personality factors were not significantly associated with conspiracy beliefs if effect sizes are aggregated. Considerable heterogeneity in designs and operationalization characterizes the field. [36] This article provides an overview of instrumentation, study designs, and current state of knowledge in an effort toward advancement and consensus in the study of conspiracy beliefs.

Personality traits influence human behaviour across a broad range of situations and are consequently relevant to many theoretical and applied disciplines [. 5. 6]. In this perspective piece, we provide an overview of the logic underpinning personality measurement and review major personality taxonomies. We provide an extensive set of recommendations for researchers and practitioners on when and how to use measures of personality traits. [7] We overview a range of taxonomic representations of personality structure focusing particularly on hierarchical representations and five and six factor models such as the Big Five and HEXACO models. We review the various strengths and weaknesses of each approach. Results The review outlines the major reasons for the dominance of the Big Five model, and suggests it is a good descriptive framework for studying personality in general. However we suggest that researchers and practitioners also consider alternative taxonomic personality representations such as the HEXACO. We provide a range of scenarios whereby alternative frameworks will be more appropriate than the Big Five and offer recommendations both for choosing measures in general and for implementing studies examining personality facets. Conclusion Whilst the Big Five represents an excellent general personality framework that is appropriate across multiple situations, researchers and practitioners should be aware of alternative measures and utilise them where appropriate [8].

This study investigates the moderating effects of tourist novelty-seeking tendencies on the relationships among destination image, satisfaction, and short- and long-term revisit intentions. Using survey data collected in 2009 from 450 European visitors to Mediterranean destinations, a theoretically derived structural path model was examined [11]. Cluster analysis and discriminant analysis were used to identify three groups of tourists based on their novelty-seeking tendencies (high, medium, and low novelty seekers). The moderating effects of novelty-seeking tendencies on the structural path model were examined by means of multigroup invariance analysis. Tourists' novelty-seeking tendencies have a moderating effect on the causal relationships among destination image, satisfaction, and revisit intentions. The effect of destination image on visitor satisfaction, as well as satisfaction on short-term revisit intentions, is significantly weaker for high novelty seekers as compared to low novelty seekers [46, 47, 48, 49, 50]. Thus, destination managers need to consider the novelty-seeking tendencies of their market segments as this affects revisit intentions.

3. METHODOLOGY

i) Proposed Work:

The project proposes an advanced solution for automatically identifying the personality trait of novelty seeking (NS) from online travel reviews. It introduces a classification framework and utilizes the BERT-BiGRU deep learning model [24], employing computational techniques to efficiently process and analyze unstructured text data. This approach enhances accuracy, speed, and scalability, providing a more effective alternative to manual classification methods. The project extends its capabilities with the integration of hybrid models, specifically "BERT CNN-BI-GRU" and "BERT-LSTM-GRU," where the latter attains an impressive 99% accuracy for enhanced novelty detection [24, 27, 31]. These hybrid models leverage the power of BERT along with various neural network architectures to capture intricate patterns in online travel reviews. The inclusion of a user-friendly Flask framework with SQLite integration enhances practical usability, providing a seamless experience for user testing, signup, and signin processes. This extension not only contributes to improved novelty detection but also emphasizes accessibility and user interaction in deep learning applications.

ii) System Architecture:

IJARST
International Journal For Advanced Research In Science & Technology
A peer reviewed international journal www.ijarst.in
ISSN: 2457-0362

The system architecture encompasses a comprehensive approach to automatically detect novelty-seeking traits within online travel reviews. Beginning with the collection and cleaning of diverse text data, the process involves labeling based on specified personality traits. The core of the architecture integrates a BERT-BiGRU deep learning model, leveraging bidirectional contextual understanding and sequential dependencies. The model is trained on labeled data, and the BiGRU layer captures intricate patterns [24, 26, 27, 28, 31]. The Softmax layer provides output probabilities for each personality trait. Evaluation metrics ensure model effectiveness, and the final output includes labeled text denoting predicted traits. This end-to-end system facilitates insights generation and integration into tourism industry applications.

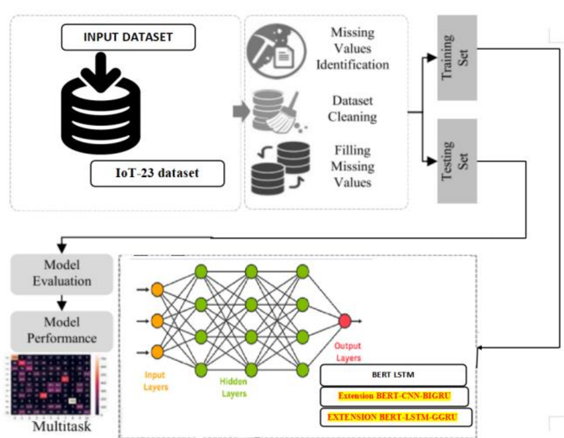


Fig 1 Proposed architecture

iii) Dataset collection:

In order to reduce the noise of experimental data, we deleted advertisements and duplicate reviews, resulting in a final experimental dataset of 28959 reviews. After collecting the data required by the experiment, the data is usually required to be preprocessed. Due to good review mechanism of the TripAdvisor, the probability of noise data and advertisements was greatly reduced. In the process of preprocessing English text, stop words refer to filtering out some frequently used but meaningless words. The purpose is to reduce the dimension of feature selection attributes, so as to reduce the amount of system calculations and improve the efficiency of analysis results. Stop words mainly include articles, prepositions, numerals, interjections, etc. For example, common English stop words include ''a \ an'', ''the'', ''of \ off'' and so on. Sometimes, in practical applications, some real words that have practical meaning but have little effect on the analysis results can be removed. Lowercase need to be converted to uppercase.

	content	label	type
0	Wow what an amazing walk on the Great Wall of ...	0	train
1	I came to spend 2 hours between 2 professional...	0	train
2	A MUST visit in one's life. History and Art fr...	1	train
3	It's was very peaceful and beautiful, go with ...	0	train
4	It is beautiful lake in all seasons. Beautiful...	0	train
...	...	...	...
3995	I visited it right when the official change to...	0	valid
3996	Suomenlinna is stunning historic place. We wen...	1	valid
3997	Milcha/Mike was funny, really knowledgeable an...	1	valid
3998	From the Helsinki market place there is a ferr...	1	valid
3999	Even though there were people there at sunrise...	1	valid

4000 rows × 3 columns

Fig 2 REVIEWS dataset

iv) Data Processing:

Data processing involves transforming raw data into valuable information for businesses. Generally, data scientists process data, which includes collecting, organizing, cleaning, verifying, analyzing, and converting it into readable formats such as graphs or documents. Data processing can be done using three methods i.e., manual, mechanical, and electronic. The aim is to increase the value of information and facilitate decision-making. This enables businesses to improve their operations and make timely strategic decisions. Automated data processing solutions, such as computer software programming, play a significant role in this. It can help turn large amounts of data, including big data, into meaningful insights for quality management and decision-making.

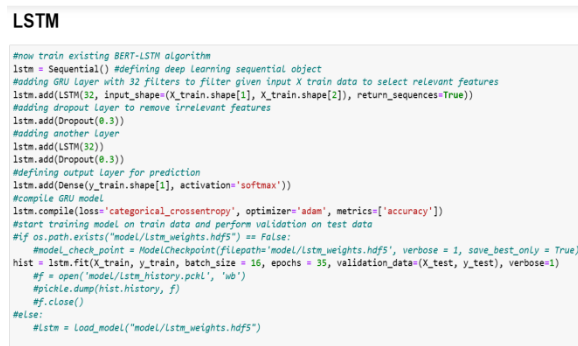
v) Feature selection:

Feature selection is the process of isolating the most consistent, non-redundant, and relevant features to use in model construction. Methodically reducing the size of datasets is important as the size and variety of datasets continue to grow. The main goal of feature selection is to improve the performance of a predictive model and reduce the computational cost of modeling.

Feature selection, one of the main components of feature engineering, is the process of selecting the most important features to input in machine learning algorithms. Feature selection techniques are employed to reduce the number of input variables by eliminating redundant or irrelevant features and narrowing down the set of features to those most relevant to the machine learning model. The main benefits of performing feature selection in advance, rather than letting the machine learning model figure out which features are most important.

vi) Algorithms:

Long Short-Term Memory (LSTM) is a type of recurrent neural network designed to address challenges associated with capturing long-term dependencies in sequential data. It introduces a memory cell that can store information over extended periods. The LSTM has three gates – input gate, forget gate, and output gate – which control the flow of information into, out of, and within the cell state. The model uses these gates to decide what information to remember and what to forget, making it particularly effective in tasks where understanding long-range dependencies is crucial, such as natural language processing.


LSTM

```
#now train existing BERT-LSTM algorithm
lstm = Sequential() #defining deep learning sequential object
#adding GRU layer with 32 filters to filter given input X train data to select relevant features
lstm.add(LSTM(32, input_shape=(X_train.shape[1], X_train.shape[2]), return_sequences=True))
#adding dropout layer to remove irrelevant features
lstm.add(Dropout(0.3))
#adding another layer
lstm.add(LSTM(32))
lstm.add(Dropout(0.3))
#defining output layer for prediction
lstm.add(Dense(y_train.shape[1], activation='softmax'))
#compile GRU model
lstm.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
#start training model on train data and perform validation on test data
#if os.path.exists("model/lstm_weights.hdf5") == False:
    #model_check_point = ModelCheckpoint(filepath='model/lstm_weights.hdf5', verbose = 1, save_best_only = True)
hist = lstm.fit(X_train, y_train, batch_size = 16, epochs = 35, validation_data=(X_test, y_test), verbose=1)
    #f = open('model/lstm_history.pckl', 'wb')
    #pickle.dump(hist.history, f)
    #f.close()
#else:
    #lstm = load_model("model/lstm_weights.hdf5")
```

Fig 3 LSTM

Bidirectional Gated Recurrent Unit (BiGRU) [27, 33, 34] is a type of recurrent neural network that enhances traditional Gated Recurrent Units (GRUs) by processing input data in both forward and backward directions. The GRU has two gates – update gate and reset gate – which control the flow of information within the hidden state. By processing the input sequence bidirectionally, the BiGRU captures dependencies from both past and future contexts. This bidirectional approach helps the model better understand the overall context of the input sequence, improving its ability to capture relevant patterns and features.

IJARST
International Journal For Advanced Research In Science & Technology
A peer reviewed international journal
www.ijarst.in
ISSN: 2457-0362

BiGRU

```
#now train propose BERT-BiGRU algorithm
gru_bilstm = Sequential() #defining deep learning sequential object
#adding GRU layer with 32 filters to filter given input X train data to select relevant features
gru_bilstm.add(Bidirectional(GRU(32, input_shape=(X_train.shape[1], X_train.shape[2]), return_sequences=True)))
#adding dropout layer to remove irrelevant features
gru_bilstm.add(Dropout(0.3))
#adding another layer
gru_bilstm.add(Bidirectional(GRU(32)))#adding bidirectional-GRU layer and peform training on X_train Bert data
gru_bilstm.add(Dropout(0.3))
#defining output layer for prediction
gru_bilstm.add(Dense(y_train.shape[1], activation='softmax'))
#compile GRU model
gru_bilstm.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
#start training model on train data and perform validation on test data
#if os.path.exists("model/bigru_weights.hdf5") == False:
    #model_check_point = ModelCheckpoint(filepath='model/bigru_weights.hdf5', verbose = 1, save_best_only = True)
hist = gru_bilstm.fit(X_train, y_train, batch_size = 16, epochs = 35, validation_data=(X_test, y_test), verbose=1)
    #f = open('model/bigru_history.pckl', 'wb')
    #pickle.dump(hist.history, f)
    #f.close()
#else:
    #gru_bilstm = load_model("model/bigru_weights.hdf5")
```

Fig 4 BiGRU

The combination of LSTM and GRU leverages the strengths of both recurrent neural network architectures. LSTM excels at capturing long-term dependencies, while GRU, being computationally less intensive, is effective at modeling shorter-term dependencies. By stacking these layers together, the model aims to benefit from the complementary capabilities of each architecture. [25, 26, 27] The LSTM layers capture and remember long-range dependencies, while the GRU layers efficiently capture more immediate dependencies. This hybrid approach is often used to enhance the overall performance of the model in tasks that involve understanding complex sequential patterns.

LSTM + GRU

```
#now train propose BERT-BiGRU algorithm
lstmgru = Sequential() #defining deep learning sequential object
#adding GRU layer with 32 filters to filter given input X train data to select relevant features
lstmgru.add(Bidirectional(LSTM(32, input_shape=(X_train.shape[1], X_train.shape[2]), return_sequences=True)))
#adding dropout layer to remove irrelevant features
lstmgru.add(Dropout(0.3))
#adding another layer
lstmgru.add(Bidirectional(GRU(32)))#adding bidirectional-GRU layer and peform training on X_train Bert data
lstmgru.add(Dropout(0.3))
#defining output layer for prediction
lstmgru.add(Dense(y_train.shape[1], activation='softmax'))
#compile GRU model
lstmgru.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
#start training model on train data and perform validation on test data
#if os.path.exists("model/bigru_weights.hdf5") == False:
    #model_check_point = ModelCheckpoint(filepath='model/bigru_weights.hdf5', verbose = 1, save_best_only = True)
hist = lstmgru.fit(X_train, y_train, batch_size = 2, epochs = 35, validation_data=(X_test, y_test), verbose=1)
    #f = open('model/bigru_history.pckl', 'wb')
    #pickle.dump(hist.history, f)
    #f.close()
#else:
    #gru_bilstm = load_model("model/bigru_weights.hdf5")
```

Fig 5 LSTM + GRU

The BERT-CNN-BI-GRU represents a more sophisticated model architecture for natural language processing tasks. BERT, a pre-trained transformer model, provides contextualized word embeddings, capturing nuanced meanings based on the context of each word. The model also includes Convolutional Neural Network (CNN) layers for local feature extraction, capturing patterns in different regions of the input sequence. Additionally, Bidirectional Gated Recurrent Unit (BI-GRU) layers process the output from BERT and CNN bidirectionally [24, 27, 31], capturing dependencies from both past and future contexts. This combination aims to create a comprehensive representation of the input sequence, incorporating both local and global contextual information for improved performance in tasks like sentiment analysis or novelty detection in textual data.

Extension BERT-CNN-Bi-GRU Model

```
#now define extension model by combining two different models called BERT + CNN + BiGRU models as this CNN + bi-lstm will
#optimized features from both forward and backward direction so it will have more optimzied features and accuracy will be better
extension_model = Sequential()
#defining CNN layer
extension_model.add(Conv1D(filters=32, kernel_size = 15, activation = 'relu', input_shape = (X_train.shape[1], X_train.shape[2]))
extension_model.add(Conv1D(filters=16, kernel_size = 12, activation = 'relu'))
#adding maxpool layer
extension_model.add(MaxPooling1D(pool_size = 2))
extension_model.add(Dropout(0.3))
extension_model.add(Flatten())
extension_model.add(RepeatVector(2))
#adding bidirectional + GRU to CNN layer
extension_model.add(Bidirectional(GRU(24, activation = 'relu')))
extension_model.add(Dropout(0.3))
#defining output layer
extension_model.add(Dense(units = 33, activation = 'softmax'))
extension_model.add(Dense(units = y_train.shape[1], activation = 'softmax'))
#compile and train the model
extension_model.compile(optimizer = 'adam', loss = 'categorical_crossentropy', metrics = ['accuracy'])
#if os.path.exists("model/extension_weights.hdf5") == False:
    #model_check_point = ModelCheckpoint(filepath='model/extension_weights.hdf5', verbose = 1, save_best_only = True)
hist = extension_model.fit(X_train, y_train, batch_size = 16, epochs = 35, validation_data=(X_test, y_test), verbose=1)
    #f = open('model/extension_history.pckl', 'wb')
    #pickle.dump(hist.history, f)
    #f.close()
```

Fig 6 BERT-CNN-BI-GRU

4. EXPERIMENTAL RESULTS

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

International Journal For Advanced Research In Science & Technology
A peer reviewed international journal www.ijarst.in
IJARST ISSN: 2457-0362

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

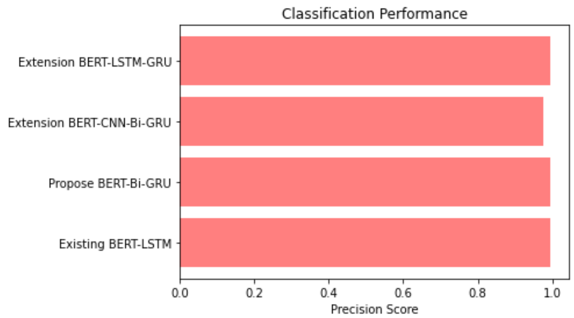


Fig 6 Precision comparison graph

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{TP}{TP + FN}$$

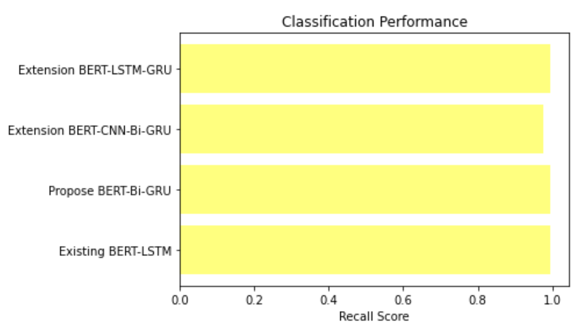


Fig 7 Recall comparison graph

Accuracy: Accuracy is the proportion of correct predictions in a classification task, measuring the overall correctness of a model's predictions.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

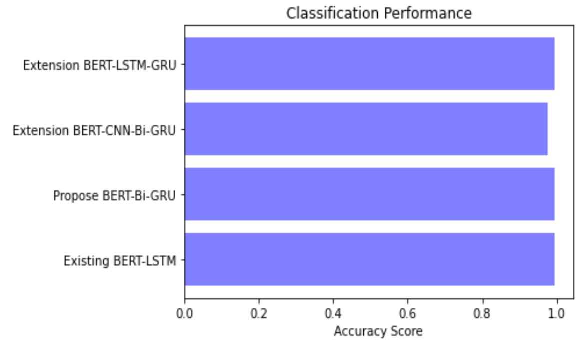


Fig 8 Accuracy graph

F1 Score: The F1 Score is the harmonic mean of precision and recall, offering a balanced measure that considers both false positives and false negatives, making it suitable for imbalanced datasets.

$$\text{F1 Score} = 2 * \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} * 100$$

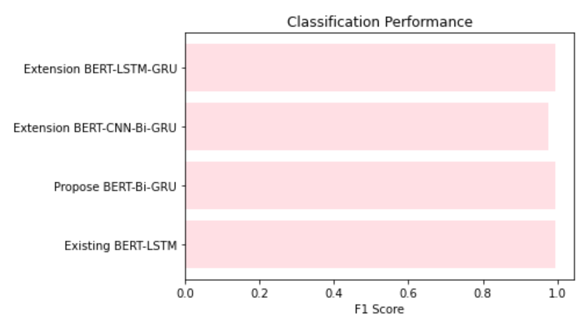


Fig 9 F1Score

ML Model	Accuracy	Precision	Recall	f1_score
Existing BERT-LSTM Model	0.994	0.994	0.994	0.994
Propose BERT-Bi-GRU Model	0.995	0.995	0.995	0.995
Extension BERT-CNN-Bi-GRU Model	**0.975**	**0.975**	**0.975**	**0.975**
Extension BERT-LSTM-GRU Model	**0.994**	**0.994**	**0.994**	**0.994**

Fig 10 Performance Evaluation

Fig 11 Home page

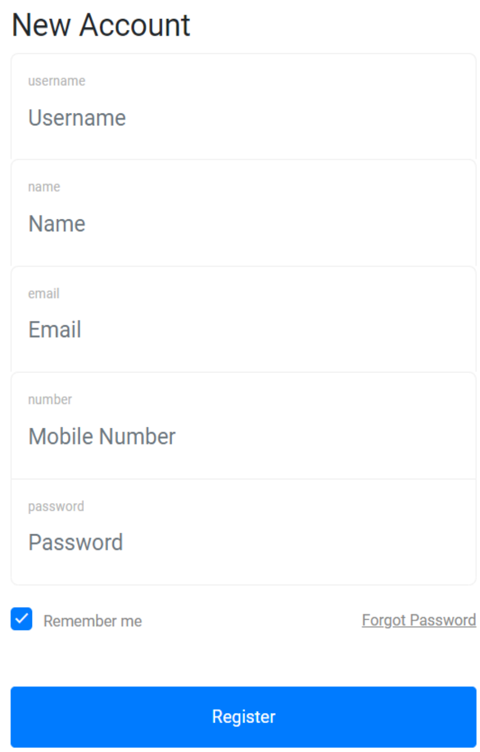


Fig 12 Signin page

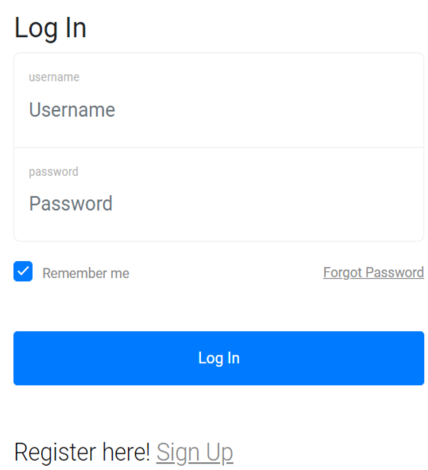


Fig 13 Login page

International Journal For Advanced Research In Science & Technology
A peer reviewed international journal www.ijarst.in
IJARST
ISSN: 2457-0362

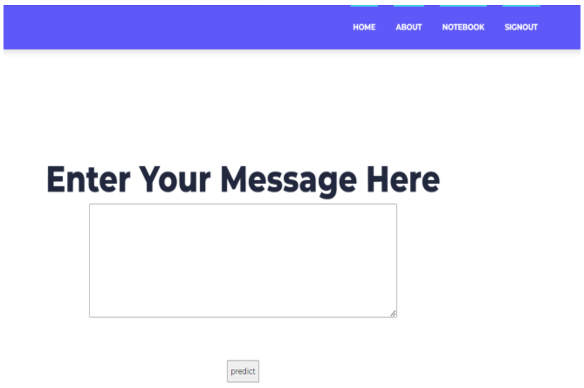


Fig 14 User input

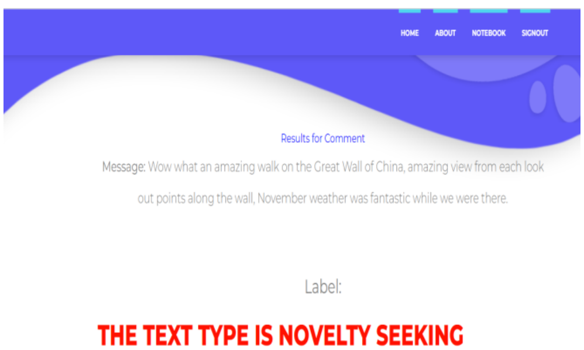


Fig 15 Predict result for given input

5. CONCLUSION

Combining multiple deep learning algorithms in the project resulted in a significant enhancement of accuracy when predicting Novelty Seeking (NS) traits from online travel reviews. NS traits are essential in comprehending travelers' behaviors and preferences. By leveraging various algorithms such as LSTM, BiGRU [26], and hybrid models like LSTM+GRU, the project aimed to capitalize on the strengths of each algorithm, leading to a more comprehensive understanding of the textual data. This amalgamation likely allowed the model to capture diverse patterns and nuances within the reviews, resulting in more accurate predictions of NS traits. Automated identification of NS behaviors within travel reviews holds practical implications for both travelers and travel organizations. For travelers, this analysis can assist in choosing destinations that align with their preferences for novel experiences. It helps them find locations or activities that cater to their inclination towards seeking new and unique experiences during travel. For travel organizations, understanding NS behaviors aids in making informed decisions regarding the development of new offerings, marketing strategies, and anticipating demand patterns. This knowledge enables them to tailor their services or products to better cater to the preferences of travelers seeking novelty. The success achieved through the hybrid model combining diverse deep learning techniques indicates potential avenues for further research and development. This suggests that integrating various deep learning architectures and ensemble methods can lead to improvements in accuracy and efficiency when analyzing behavioral patterns within textual data [20, 24]. It opens up opportunities for exploring new combinations of algorithms, refining ensemble strategies, and investigating the applicability of these methods in other domains beyond travel reviews. The success of this project paves the way for continued advancements in the utilization of deep learning for understanding nuanced behaviors from textual data across various domains.

6. FUTURE SCOPE

he future scope involves enhancing the tourist destination recommendation system by optimizing it based on the identified novelty-seeking (NS) personality trait. This optimization may include the development of user groups with NS, refining user portrait understanding, and implementing precision marketing strategies. By tailoring recommendations to users with specific personality traits, the system can offer more personalized and engaging travel suggestions. Further research can explore synergies between deep learning methods, such as the BERT-BiGRU model [33], and traditional personality evaluation methods like questionnaires and interviews. This hybrid approach can overcome the limitations of subjective and static personality measurement methods, improving efficiency and accuracy in identifying NS. Integrating multiple sources of data can lead to a more comprehensive understanding of an individual's personality. The application of the deep learning model can be extended beyond online travel reviews to various domains where personality traits can be inferred through text information [20, 24]. This includes product reviews, employee comments, and moral event analysis. Expanding the scope of the model's application demonstrates its versatility and potential for providing valuable insights in diverse contexts beyond the tourism industry. The project's findings have the potential to inspire future research in text classification based on deep learning, personality trait recognition, and novelty seeking. Contributions to the development of computational techniques in psychology and marketing can fuel advancements in understanding user behavior, preferences, and motivations. This, in turn, can lead to the creation of more sophisticated and effective systems in various fields.

REFERENCES

[1] Y. Chang, R.-J. Hou, K. Wang, A. P. Cui, and C.-B. Zhang, ‘‘Effects of intrinsic and extrinsic motivation on social loafing in online travel communities,’’ Comput. Hum. Behav., vol. 109, Aug. 2020, Art. no. 106360.

[2] G. Assaker, ‘‘Age and gender differences in online travel reviews and user-generated-content (UGC) adoption: Extending the technology acceptance model (TAM) with credibility theory,’’ J. Hospitality Marketing Manag., vol. 29, no. 4, pp. 428–449, May 2020, doi: 10.1080/19368623.2019.1653807.

[3] M. J. Garcia, J. R. Chico, A. R. P. Sanchez, and J. A. L. Sanchez, ‘‘Does electronic word-of-mouth differently influence traditional economy vs. collaborative economy tourist accommodation? An empirical study,’’ J. Quality Assurance Hospitality Tourism, vol. 23, no. 3, pp. 771–795, 2021, doi: 10.1080/1528008X.2021.1913692.

[4] I. Sagovnovic and S. Kovacic, ‘‘Predicting travel motivation with personality and personal values—The roles of big five plus honesty/humility personality traits and Kahle’s values,’’ Int. J. Hospitality Tourism Admin., pp. 1–30, Jan. 2022.

[5] D. J. Yoon, ‘‘Rude customers and service performance: Roles of motivation and personality,’’ Service Industries J., vol. 42, nos. 1–2, pp. 81–106, Jan. 2022.

[6] A. Goreis and M. Voracek, ‘‘A systematic review and meta-analysis of psychological research on conspiracy beliefs: Field characteristics, measurement instruments, and associations with personality traits,’’ Frontiers Psychol., vol. 10, p. 205, Feb. 2019.

[7] J. Anglim and P. O'connor, ''Measurement and research using the big five, HEXACO, and narrow traits: A primer for researchers and practitioners,'' Austral. J. Psychol., vol. 71, no. 1, pp. 16–25, Mar. 2019.

[8] Y. Mehta, N. Majumder, A. Gelbukh, and E. Cambria, ''Recent trends in deep learning based personality detection,'' Artif. Intell. Rev., vol. 53, no. 4, pp. 2313–2339, Apr. 2020.

[9] E. C. Hirschman, ''Innovativeness, novelty seeking, and consumer creativity,'' J. Consum. Res., vol. 7, no. 3, pp. 283–295, 1980.

[10] S. S. Jang and R. Feng, ''Temporal destination revisit intention: The effects of novelty seeking and satisfaction,'' Tourism Manag., vol. 28, no. 2, pp. 580–590, Apr. 2007.

[11] G. Assaker and R. Hallak, ''Moderating effects of tourists novelty-seeking tendencies on destination image, visitor satisfaction, and short- and longterm revisit intentions,'' J. Travel Res., vol. 52, no. 5, pp. 600–613, Sep. 2013.

[12] A. Lloyd, R. McKay, C. L. Sebastian, and J. H. Balsters, ''Are adolescents more optimal decision-makers in novel environments? Examining the benefits of heightened exploration in a patch foraging paradigm,'' Develop. Sci., vol. 24, no. 4, p. e13075, 2021.

[13] E. E. Pujiastuti, ''Novelty seeking to predict behavior intention in rural destination,'' Jurnal Bisnis Dan Manajemen, vol. 7, no. 2, pp. 1–13, Nov. 2020.

[14] W.-J. Seo, L. A. Lewin, B. Moon, and B.-Y. Moon, ''Moderating effects of affective image on relationship between novelty-seeking and behavioural intentions of runners,'' South Afr. J. Res. Sport, Phys. Educ. Recreation, vol. 40, no. 3, pp. 105–120, 2018.

[15] Q. N. Nguyen, H. L. Nguyen, and T. D. H. Le, ''Relationships among novelty seeking, satisfaction, return intention, and willingness to recommend of foreign tourists in Vietnam,'' Manag. Sci. Lett., vol. 10, no. 10, pp. 2249–2258, 2020.

[16] L.-H. Lee, Y. Lu, P.-H. Chen, P.-L. Lee, and K.-K. Shyu, ''NCUEE at MEDIQA 2019: Medical text inference using ensemble BERT-BiLSTMattention model,'' in Proc. 18th BioNLP Workshop Shared Task, 2019, pp. 528–532.

[17] K. Kowsari, K. J. Meimandi, M. Heidarysafa, S. Mendu, L. Barnes, and D. Brown, ''Text classification algorithms: A survey,'' Information, vol. 10, no. 4, p. 150, Apr. 2019.

[18] A. Rantanen, J. Salminen, F. Ginter, and B. J. Jansen, ''Classifying online corporate reputation with machine learning: A study in the banking domain,'' Internet Res., vol. 30, no. 1, pp. 45–66, Nov. 2019, doi: 10.1108/intr-07-2018-0318.

[19] S. Li, M. You, D. Li, and J. Liu, ''Identifying coal mine safety production risk factors by employing text mining and Bayesian network techniques,'' Process Saf. Environ. Protection, vol. 162, pp. 1067–1081, Jun. 2022.

[20] C. Zhang, T. Tong, and Y. Bu, ''Examining differences among book reviews from various online platforms,'' Online Inf. Rev., vol. 43, no. 7, pp. 1169–1187, 2019.

International Journal For Advanced Research In Science & Technology
A peer reviewed international journal www.ijarst.in
IJARST ISSN: 2457-0362

[21] K. Zvarevashe and O. O. Olugbara, ‘‘A framework for sentiment analysis with opinion mining of hotel reviews,’’ in Proc. Conf. Inf. Commun. Technol. Soc. (ICTAS), Mar. 2018, pp. 1–4.

[22] Y. Xie and F. Xiang, ‘‘An improved approach based on dynamic mixed sampling and transfer learning for topic recognition: A case study on online patient reviews,’’ Online Inf. Rev., vol. 46, no. 6, pp. 1017–1033, Sep. 2022

[23] S. Ilyas, A. A. Shah, and A. Sohail, ‘‘Order management system for time and quantity saving of recipes ingredients using GPS tracking systems,’’ IEEE Access, vol. 9, pp. 100490–100497, 2021, doi: 10.1109/ACCESS.2021.3090808.

[24] C.-X. Wan and B. Li, ‘‘Financial causal sentence recognition based on BERT-CNN text classification,’’ J. Supercomput., vol. 78, no. 5, pp. 6503–6527, Apr. 2022, doi: 10.1007/s11227-021-04097-5.

[25] J. Chen, Y. Zhang, J. Wu, W. Cheng, and Q. Zhu, ‘‘SOC estimation for lithium-ion battery using the LSTM-RNN with extended input and constrained output,’’ Energy, vol. 262, Jan. 2023, Art. no. 125375.

[26] C. Xu, F. Yuan, and S. Chen, ‘‘BJBN: BERT-JOIN-BiLSTM networks for medical auxiliary diagnostic,’’ J. Healthcare Eng., vol. 2022, pp. 1–7, Jan. 2022, doi: 10.1155/2022/3496810.

[27] B. Gupta, P. Prakasam, and T. Velmurugan, ‘‘Integrated BERT embeddings, BiLSTM-BiGRU and 1-D CNN model for binary sentiment classification analysis of movie reviews,’’ Multimedia Tools Appl., vol. 81, no. 23, pp. 33067–33086, 2022.

[28] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, ‘‘BERT: Pre-training of deep bidirectional transformers for language understanding,’’ 2018, arXiv:1810.04805.

[29] K. Chatsiou, ‘‘Text classification of manifestos and COVID-19 press briefings using BERT and convolutional neural networks,’’ 2020, arXiv:2010.10267.

[30] W. H. Bangyal, R. Qasim, N. U. Rehman, Z. Ahmad, H. Dar, L. Rukhsar, Z. Aman, and J. Ahmad, ‘‘Detection of fake news text classification on COVID-19 using deep learning approaches,’’ Comput. Math. Methods Med., vol. 2021, pp. 1–14, Nov. 2021.

[31] P. K. Verma, P. Agrawal, V. Madaan, and R. Prodan, ‘‘MCred: Multi-modal message credibility for fake news detection using BERT and CNN,’’ J. Ambient Intell. Humanized Comput., pp. 1–13, Jul. 2022.

[32] R. Cai, B. Qin, Y. Chen, L. Zhang, R. Yang, S. Chen, and W. Wang, ‘‘Sentiment analysis about investors and consumers in energy market based on BERT-BiLSTM,’’ IEEE Access, vol. 8, pp. 171408–171415, 2020, doi: 10.1109/access.2020.3024750.

[33] Q. Yu, Z. Wang, and K. Jiang, ‘‘Research on text classification based on BERT-BiGRU model,’’ J. Phys., Conf., vol. 1746, no. 1, Jan. 2021, Art. no. 012019, doi: 10.1088/1742-6596/1746/1/012019.

[34] N.-N. Zhang and Y. Xing, ‘‘Questions and answers on legal texts based on BERT-BiGRU,’’ J. Phys., Conf., vol. 1828, no. 1, Feb. 2021, Art. no. 012035.

[35] J. Dai and C. Chen, ‘‘Text classification system of academic papers based on hybrid BERT-BiGRU model,’’ in Proc. 12th Int. Conf. Intell. HumanMach. Syst. Cybern. (IHMSC), Aug. 2020, pp. 40–44.

[36] J. D. Moreno, J. Á. Martínez-Huertas, R. Olmos, G. Jorge-Botana, and J. Botella, ‘‘Can personality traits be measured analyzing written language? A meta-analytic study on computational methods,’’ Personality Individual Differences, vol. 177, Jul. 2021, Art. no. 110818.

[37] J. Sun, H. A. Schwartz, Y. Son, M. L. Kern, and S. Vazire, ‘‘The language of well-being: Tracking fluctuations in emotion experience through everyday speech,’’ J. Personality Social Psychol., vol. 118, no. 2, p. 364, 2020.

[38] T. Smartt, S. Talaifar, and S. D. Gosling, ‘‘Dostoyevsky’s conjecture: Evaluating personality impressions based on laughter,’’ J. Nonverbal Behav., vol. 46, pp. 383–397, Aug. 2022.

[39] M. E. Tabacchi, B. Caci, M. Cardaci, and V. Perticone, ‘‘Early usage of Pokémon go and its personality correlates,’’ Comput. Hum. Behav., vol. 72, pp. 163–169, Jul. 2017.

[40] K. N. P. Kumar and M. L. Gavrilova, ‘‘Latent personality traits assessment from social network activity using contextual language embedding,’’ IEEE Trans. Computat. Social Syst., vol. 9, no. 2, pp. 638–649, Apr. 2021.

[41] M. Romeo, D. H. García, T. Han, A. Cangelosi, and K. Jokinen, ‘‘Predicting apparent personality from body language: Benchmarking deep learning architectures for adaptive social human–robot interaction,’’ Adv. Robot., vol. 35, no. 19, pp. 1167–1179, Oct. 2021.

[42] R. Subramanian, J. Wache, M. K. Abadi, R. L. Vieriu, S. Winkler, and N. Sebe, ‘‘ASCERTAIN: Emotion and personality recognition using commercial sensors,’’ IEEE Trans. Affect. Comput., vol. 9, no. 2, pp. 147–160, Apr./Jun. 2018.

[43] X. Xue, J. Feng, and X. Sun, ‘‘Semantic-enhanced sequential modeling for personality trait recognition from texts,’’ Int. J. Speech Technol., vol. 51, no. 11, pp. 7705–7717, Nov. 2021.

[44] D. Pizzolli and C. Strapparava, ‘‘Personality traits recognition in literary texts,’’ in Proc. 2nd Workshop Storytelling, 2019, pp. 107–111.

[45] L. Qiu, J. Lu, J. Ramsay, S. Yang, W. Qu, and T. Zhu, ‘‘Personality expression in Chinese language use,’’ Int. J. Psychol., vol. 52, no. 6, pp. 463–472, Dec. 2017.

[46] T.-H. Lee and J. Crompton, ‘‘Measuring novelty seeking in tourism,’’ Ann. Tourism Res., vol. 19, no. 4, pp. 732–751, Jan. 1992.

[47] R. P. Agustina and Y. Artanti, ‘‘The role of satisfaction as a mediating variable on the effects of novelty seeking and familiarity on tourist revisit intention,’’ Diponegoro Int. J. Bus., vol. 3, no. 2, pp. 88–96, Dec. 2020.

[48] S. Zulzilah, E. Prihantoro, and C. Wulandari, ‘‘The influence of destination image, novelty seeking, and information quality in social media: The case of media news company Indonesian tourism on Instagram,’’ Asian J. Media Commun. (AJMC), vol. 3, no. 1, pp. 23–32, 2019.

[49] M. L. Azic and N. Sustar, ‘‘Loyalty to holiday style: Motivational determinants,’’ Tourism Rev., vol. 77, no. 1, pp. 239–255, 2021.

[50] P. H. Pearson, ‘‘Relationships between global and specified measures of novelty seeking,’’ J. Consulting Clin. Psychol., vol. 34, no. 2, pp. 199–204, Apr. 1970.

[51] M. Ludwig, M. Richter, J. Goltermann, R. Redlich, J. Repple, C. Flint, D. Grotegerd, K. Koch, E. J. Leehr, S. Meinert, C. Hulsmann, V. Enneking, H. Kugel, T. Hahn, B. T. Baune, U. Dannlowski, and N. Opel, ‘‘Novelty seeking is associated with increased body weight and orbitofrontal grey matter volume reduction,’’ Psychoneuroendocrinology, vol. 126, Apr. 2021, Art. no. 105148.

[52] F.-Z. Zhuang, Y. M. Zhou, H. C. Ying, F. Z. Zhang, X. Ao, X. Xie, Q. He, and H. Xiong, ‘‘Sequential recommendation via cross-domain novelty seeking trait mining,’’ J. Comput. Sci. Technol., vol. 35, pp. 305–319, Mar. 2020.

[53] S. Kitouna and Y.-G. Kim, ‘‘Tourists novelty-seeking motivation in naturebased tourism destinations: The case of Vang Vieng city in Laos,’’ Int. J. Tourism Hospitality Res., vol. 31, no. 10, pp. 45–58, Oct. 2017.

[54] G. Sheppard, K.-L. Williams, B. Metcalfe, M. Clark, M. Bromley, P. Pageau, M. Woo, Y. Yi, A. J. Devasahayam, and A. Dubrowski, ‘‘Using Kane’s framework to build an assessment tool for undergraduate medical student’s clinical competency with point of care ultrasound,’’ BMC Med. Educ., vol. 23, no. 1, pp. 1–8, Jan. 2023.

[55] J. Wen, E. Thibeau-Sutre, M. Diaz-Melo, J. Samper-González, A. Routier, S. Bottani, D. Dormont, S. Durrleman, N. Burgos, and O. Colliot, ‘‘Convolutional neural networks for classification of Alzheimer’s disease: Overview and reproducible evaluation,’’ Med. Image Anal., vol. 63, Jul. 2020, Art. no. 101694.

[56] D. Valero-Carreras, J. Alcaraz, and M. Landete, ‘‘Comparing two SVM models through different metrics based on the confusion matrix,’’ Comput. Oper. Res., vol. 152, Apr. 2023, Art. no. 106131.

[57] A. A. Shah, M. K. Ehsan, A. Sohail, and S. Ilyas, ‘‘Analysis of machine learning techniques for identification of post translation modification in protein sequencing: A review,’’ in Proc. Int. Conf. Innov. Comput. (ICIC), Nov. 2021, pp. 1–6, doi: 10.1109/ICIC53490.2021.9693020.

[58] A. Sohail, N. A. Nawaz, A. A. Shah, S. Rasheed, S. Ilyas, and M. K. Ehsan, ‘‘A systematic literature review on machine learning and deep learning methods for semantic segmentation,’’ IEEE Access, vol. 10, pp. 134557–134570, 2022, doi: 10.1109/ACCESS.2022.3230983.

[59] D. Zheng, G. Pang, B. Liu, L. Chen, and J. Yang, ‘‘Learning transferable deep convolutional neural networks for the classification of bacterial virulence factors,’’ Bioinformatics, vol. 36, no. 12, pp. 3693–3702, Jun. 2020, doi: 10.1093/bioinformatics/btaa230.

[60] B. Kandimalla, S. Rohatgi, J. Wu, and C. L. Giles, ‘‘Large scale subject category classification of scholarly papers with deep attentive neural networks,’’ Frontiers Res. Metrics Anal., vol. 5, Feb. 2021, Art. no. 600382.

[61] B. Jang, I. Kim, and J. W. Kim, ‘‘Word2vec convolutional neural networks for classification of news articles and tweets,’’ PLoS ONE, vol. 14, no. 8, Aug. 2019, Art. no. e0220976.

[62] A. S. Kale, V. Pandya, F. Di Troia, and M. Stamp, ‘‘Malware classification with Word2Vec, HMM2Vec, BERT, and ELMo,’’ J. Comput. Virol. Hacking Techn., pp. 1–16, Apr. 2022.

[63] B.-T. Pham-Hong and S. Chokshi, ‘‘PGSG at SemEval-2020 task 12: BERT-LSTM with tweets pretrained model and noisy student training method,’’ in Proc. 14th Workshop Semantic Eval., 2020, pp. 2111–2116.

[64] X. Deng, Q. Liu, Y. Deng, and S. Mahadevan, ‘‘An improved method to construct basic probability assignment based on the confusion matrix for classification problem,’’ Inf. Sci., vol. 340, pp. 250–261, May 2016.