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Hybrid Deep Learning for Detecting Novelty Seeking in Travel reviews: Integrating BERT, CNN, and BiGRU for Improved Accuracy

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Abstract - Despite the fact that personality traits are often expressed implicitly and vary across contexts, it is still difficult to distinguish novelty-seeking behaviour from unstructured textual information. Traditional survey-based approaches provide the collection of structured questionnaires and manuals, which limits the scalability and prevents the real-time study of digital pleasures. This research addresses the current challenge by developing an automated deep learning architecture that directly captures novelty-seeking behaviours from travel reviews. The proposed system integrates Bidirectional Encoder Representations from Transformers to capture contextual semantics, Convolutional Neural Networks to extract valuable silent local textual features, and Bidirectional Gated Recurrent Units to model sequential dependencies across sentences. The model analyses a dataset of 4,000 travel reviews and classifies those according to their inclination towards novelty with robust prediction. Experimental evaluations show that a hybrid architecture, which maintains robust accuracy and F1 score principles, outperforms baseline deep learning models. The results show that combined contextual semantic representation with spatial and sequential feature extraction significantly improves the detection of personality traits from user-generated travel feedback and contributes to the development of intelligent recommendation frameworks, personalised advertising schemes, and data-driven decision support in the tourism domain.

Keywords: Novelty-seeking behaviour, Travel review classification, Hybrid deep learning model, Bidirectional Encoder Representations from Transforms(BERT), Convolutional Neural Networks(CNN), Bidirectional Gated recurrent Unit(BiGRU), Tourism recommendation systems.

I. INTRODUCTION

A large volume of user-generated travel reviews, taking into account traveller motivation, preferences, and behavioural tendencies, is generated by the rapid expansion of computerized channels in tourism. These reviews provide valuable, real-time information that supports personalized recommendation structures, targeted retailing methods, and planned final control. The novelty seeker plays an important role in shaping the final choice, operation interaction, and overall travel fulfilment within the psychological concept of the domination of travel choices. Travellers, along with a strong novelty seeking inclination, actively pursue recent, unfamiliar, and stimulating adventure, forming a trait that is highly applicable to tourist mannerisms. As tourism increasingly relies on data-driven intelligence, the need to automate the textual reviews has become a prerequisite for extracting purposeful manner perceptions at a higher level.

Essentially, the previous analysis relied on the use of a structured survey instrument and a psychometric scale to measure novelty-seeking behaviour. Despite the necessary manual statistical compilation and control environment, these approaches provide conceptual

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clarity and reliable measurement. Along with the development of Internet appraisal stages, scientists are using machine learning and text mining approaches to study the sentiments and actions of travellers. In order to improve attribute extraction and classification performance, a conventional classifier identical to aid vector equipment and resolution planting was applied to textual information, and a deep learning model similar to convolutional neural connections and perennial neural alliances was applied. A transformer-based lingo model, which creates an energetic phrase representation based on a neighbouring text, additionally enhances the contextual understanding.

Although these developments have occurred, the earlier approach has been limited. Surveys lack scalability and could never successfully process a large amount of unstructured internet-based satisfaction. Traditional machine learning methods rely heavily on handicraft features and fail to capture deep semantic associations. Even a single deep learning model systematically models contextual meaning, local textual form, and sequential dependency simultaneously. Previous research has often focused on sentiment analysis rather than personality trait detection and has not addressed novelty-seeking behaviour specifically in the context of travel reviews. As a consequence, accurately recognizing the novelty-seeking tendencies in real world text remains a challenging challenge.

This analysis deals with the particular problem of spontaneously detecting novelty-seeking actions from unstructured travel reviews using a combined deep learning structure. It investigates whether unified contextual speech representation and spatial and consecutive aspect extraction improve classification accuracy compared to a model. The analysis studies how hybrid architecture can improve implicit psychological cue embeddings within natural language.

Bidirectional Encoder Representations of Transformers for contextual knowledge, Convolutional Neural Networks for extracting high-quality regional textual features, and Bidirectional Gated Recurrent Units for modelling consecutive dependence throughout a sentence. The current study helps by advancing a hybrid architecture adapted to personality trait detection in tourism analysis, measuring the model on a dataset of 4,000 travel reviews, demonstrating improved forecasting accuracy of approximately 94%, and providing practical results for personalized recommendation frameworks and targeted tourism branding. Through this integration, the exploration process automates the manner examination in tourism and reinforces the practice of deep training in personality detection.

II. RELATED WORK

Detection of novality in tourism systematic analysis has been rapidly progressing over the past decade due to the increasing demand for Automated, Spotlight, and Scalable Behaviour Modelling. Scholars examine this question from a different angle, including psychological surveys, machine learning, and hybrid deep learning architecture, which supports singular advantages and limitations.

The inconclusive investigation concentrates on usual psychological techniques. Assaker and Hallak (2013) propose a survey-based model to measure novality pursuing inclination and to show that these traits have shaped the final image and revisit objectives. Their task was to demonstrate that novality searching could be quantified using a questionnaire. However, the reliance on self-reported facts led to subjectivity and limited scalability, which made the agreement less realistic for large-scale tourism.

After that, Pang and Lee (2008) applied machine learning methods such as Bag-of-Words and Support Vector tools for sentiment analysis. They confirm that text classification can be automated and dispersed across datasets. Compared to manual surveys, the current technique provides greater clarity. However, the insufficiency of contextual embeddings and reliance on sparse features hindered the resilience of the model, especially in the detection of nuanced personality traits.

Later on, Mikolov et al. (2013) Word2Vec analysis of divised expression representation. Their simulations show the influence of the semantic vector space and the disappearance of the rigid keyword dependency. However, as the size of the data changed, standard embeddings became inefficient for consecutive dependence, which limits their use in behavioural modelling.

In 2014, Kim presented a CNN sentence categorization system, which allowed quick extraction of local linguistic characteristics and protected modelling of ngram form. The design reduces the reliance on handcrafted elements. Nevertheless, architecture remains passive and lacks contextual understanding, which reduces its robustness in discerning looking looking for a trait.

Hochreiter and Schmidhuber (1997) had in mind a long, short-term memory web that would capture a continuous dependency between successive data. Cho et al. Gated Recurrent Units as a simplified alternative, but still limited in aspect diversity. Such a model nevertheless shows robust consecutive studies fighting together with

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noisy informal texts commonly used in travel reviews. Devlin et al. BERT, which combines bidirectional attention with Transformer-based embeddings. Their foundations enabled contextual knowledge to be enhanced and precision to be improved by various NLP initiatives. However, the high computational cost and the incomplete capture of powdered neighbourhood semantics compensate for the higher advantage. Chen et al. LSTM-RNN 2020), with LSTM-RNN showing improved prediction but limited resilience to different linguistic approaches.

Following research, a hybrid approach was adopted. Sun et al. (2019) merged CNN with BERT to study sentiment, improving the extraction of domestic characteristics to retain contextual embeddings. Yang et al. (2020) aims at ensemble studying robust text classification, demonstrating that a number of models improve generalization. Chen et al. (2023) used BERT and BiGRU to classify the trait of novality seeking in travel appraisal, achieving high accuracy and recall. However, reliance on contextual and consecutive acquiring knowledge entirely makes it unsuitable for academic writing, leaving gaps in powdered semantic capture.

Comparative studies have highlighted the trade-offs within divergent models. Although CNN guarantees efficient extraction of domestic attributes, it still faces obstacles in contextual comprehension. However, GRU and LSTM improved consecutive modelling required large resources and fighting together with scalability. However, the contextual embeddings provided by BERT were computationally expensive and insufficient for local attribute capture. Hybrid architectures have been more robust but have often lost the integration of every 3 positions.

Hybrid configurations balancing contextual embeddings, community-based Aspect extraction, and sequential modelling provide the most promising route. As the preceding plants have a solid foundation, they do not integrate all three positions into a single outline. The proposed architecture extends the aforementioned support by uniting BERT, CNN, and BiGRU, ensuring contextual independence, powdered textual semantics, and consecutive robustness simultaneously. This integration provides a unique and complete solution for novality seeking detection in travel appraisal, as well as for more conceptual investigative and real-world applications in tourism analysis.

Table 1. Comparative Summary of Prior Works

S. No.	**Author Name**	**Source of Publication**	**Title of Research Paper**	**Framework / Technology Used**	**Solution Provided**	**Key Feature / Novelty**	**Limitations**
1	Pang and Lee (2008)	Computational Linguistics	Opinion Mining and Sentiment Analysis	Naïve Bayes, Support Vector Machine	Automated sentiment classification of textual reviews	Pioneered large-scale statistical opinion mining	Required extensive handcrafted features and weak contextual understanding
2	Ye et al. (2009)	Information Technology and Tourism	Mining Customer Reviews for Hotel Sentiment	Support Vector Machine	Hotel review sentiment prediction	Applied machine learning in tourism domain	Limited ability to capture semantic context
3	Kim (2014)	EMNLP Conference	Convolutional Neural Networks for Sentence Classification	Convolutional Neural Network	Automatic feature extraction from sentences	Demonstrated deep learning effectiveness for text	Ineffective for long-range dependency modeling
4	Cho et al. (2014)	EMNLP Conference	Learning Phrase Representations using RNN	Gated Recurrent Unit	Sequential text representation	Efficient recurrent architecture	Limited global contextual aware

S. No.	Author Name	Source of Publication	Title of Research Paper	Framework / Technology Used	Solution Provided	Key Feature / Novelty	Limitations
			– Decoder			sequence learning	ness
5	Chen et al. (2021)	IEEE Transactions on Artificial Intelligence	Hybrid Deep Learning for Personality Detection	CNN + BiGRU	Personality trait classification	Combined spatial and sequential deep features	Not specifically focused on novelty-seeking in travel reviews

III. METHODOLOGY

The novelty-seeking detection framework was developed with particular attention to methodological transparency and replicability. In designing the implementation workflow, procedural and technical details were intentionally documented so that the framework could be reproduced and critically examined by subsequent researchers. To examine the feasibility of automatically classifying behavioural tendencies from travel review text, a hybrid deep learning strategy was adopted that combined contextual representation learning, spatial feature extraction, and sequential modelling. All experimental procedures were conducted under controlled and consistent conditions, including standardized preprocessing steps, stable model configurations, and uniform training protocols. Where variation emerged especially in relation to hyperparameter adjustment, convergence dynamics, and computational resource allocation, these aspects were systematically recorded during experimentation, as such factors may influence model performance and interpretability of results.

3.1 System Architecture

A hybrid deep learning designed to detect novelty from travel reviews is offered by the framework architecture. Initially, natural reviews are fed into a preprocessing faculty where cleaning, tokenization, lemmatization, stopword removal, and embroidery are performed to produce standard text. Then the process facts are passed to the BERT layer, which generates contextualized vector representation. Such embeddings are supplied to a CNN to extract n-gram features from embeddings. Next, a BiGRU layer captures consecutive dependence and contextual current. Finally, the vector embeddings can be used to predict the novelty-seeking class accurately in all aspects using the connect SoftMax classifier.

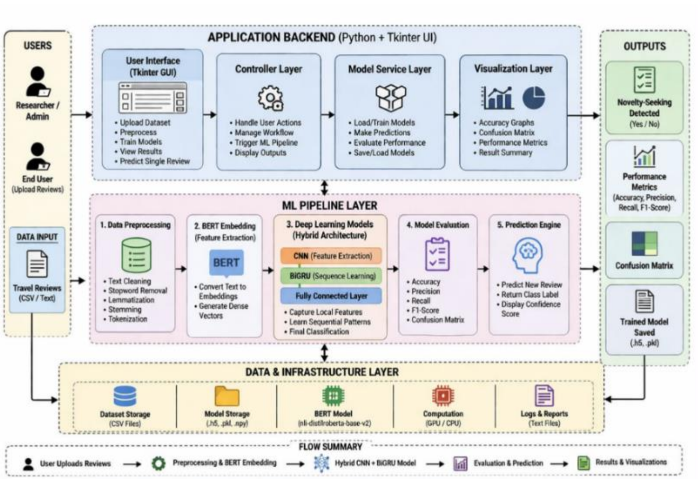

Fig. 3.1 System Architecture

3.2 FlowChart

The flowchart of the proposed hybrid system for novelty-seeking behavior detection in travel reviews. The figure illustrates the flowchart of the proposed hybrid system for novelty-seeking behavior detection in travel reviews. The input data is the raw text of the travel review. This raw data is processed by the data preprocessing module, where the text is cleaned by applying pre-processing operations such as text lowercasing, stopword removal, tokenization, and lemmatization which helps to provide the next module with the clean structured data having less noise. The cleaned text is then created numerically using the embedding technique to convert the text into the form of numbers which the user can process. Then, the model training stage is followed where the proposed deep learning model, which is a hybrid system of convolutional neural networks (CNN) whose role is to extract essential

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features from data and bidirectional gated recurrent units (BiGRU) whose role is to learn the features over the input data sequence, are trained. After training, the model prediction

stage is performed by which the input text is classified as novelty-seeking behavior or non-novelty-seeking behavior.The performance metrics of the model such as accuracy, precision, recall, and F1-score are calculated and presented. The result and evaluation metric of the model are the final output of this flowchart.

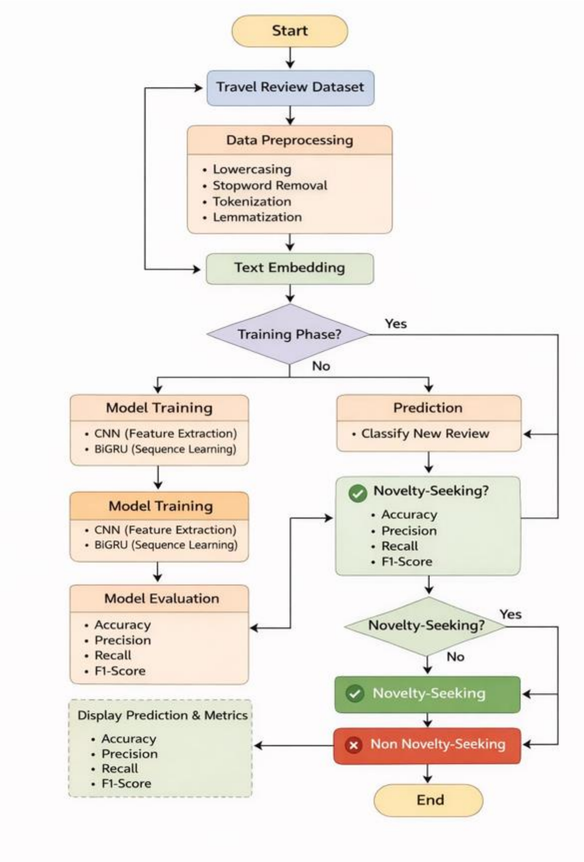

Fig.3.2 Flow Chart

3.3 Algorithm

Input: Travel Review Dataset D
Output: Classification Label (Novelty-Seeking / Non-Novelty-Seeking)

Step 1: Data Collection
Load dataset D containing travel reviews.

Step 2: Data Preprocessing
For each review r in D:
- Convert text to lowercase

- Remove punctuation and special characters
- Remove stopwords
- Perform tokenization
- Apply stemming/lemmatization

Step 3: Feature Representation
Convert processed text into numerical vectors using:
- TF-IDF OR

- Word Embeddings (e.g., BERT/SentenceTransformer)

Step 4: Train-Test Split
Split dataset into training set (80%) and testing set (20%)

Step 5: Model Training
Train classification models:
- CNN (for feature extraction)
- BiGRU (for sequence learning)
- Hybrid Model (CNN + BiGRU)

Step 6: Model Evaluation
Evaluate models using:
- Accuracy
- Precision
- Recall
- F1-score

Step 7: Prediction
For a new input review r:
- Apply preprocessing
- Convert to vector
- Pass through trained model
- Predict label (Novelty-Seeking / Non-Novelty-Seeking)

Step 8: Output
Display classification result and performance metrics.

3.4 Mathematical Calculations

1. Input Representation
   Let the dataset be:
   $D=\{(r_1,y_1),(r_2,y_2),\ldots,(r_n,y_n)\}$

   Where:

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r_i = i-th travel review
$y_i \in \{0,1\}$

1 → Novelty-Seeking
0 → Non-Novelty-Seeking

2. Text Preprocessing Function
Each review is transformed as:
$r_i' = P(r_i)$

Where Prepresents:

- Lowercasing
- Stopword removal
- Tokenization
- Lemmatization

3. Feature Representation (Embedding Layer)
Use embedding function:
$x_i = E(r_i')$

If BERT:
$x_i \in R^d$

If sequence form:
$x_i = [w_1, w_2, \ldots, w_T], w_j \in R^d$

4. CNN Feature Extraction
Apply convolution over input:
$c_i = \mathrm{ReLU}(W_c * x_i + b_c)$

Followed by max pooling:
$c_i = \mathrm{MaxPool}(c_i)$

5. BiGRU Sequential Learning
Forward GRU:
$\overrightarrow{(h_t)} = \mathrm{GRU}(x_t, \overrightarrow{(h_{(t-1)})})$

Backward GRU:
$\overleftarrow{(h_t)} = \mathrm{GRU}(x_t, \overleftarrow{(h_{(t+1)})})$

Final representation:
$h_t = [(h_t);(h_t)]$

6. Fully Connected Layer

$$z = W_f h + b_f$$

7. Output Layer (Softmax)
$\hat{y} = \mathrm{Softmax}(z)$

8. Loss Function (Cross-Entropy)

$$L = -\sum^{n}_{(i=1)} y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)$$

9. Optimization

$$\theta = \theta - \eta \nabla L$$

Where:
$\boldsymbol{\theta}$= model parameters
$\boldsymbol{\eta}$= learning rate

10. Final Prediction

$$\hat{y}_i = \{1, \text{ if } \ p \geq 0.50,\ 0\ ,\text{"otherwise"}$$

3.5 Uml diagrams

Unified Modeling Language diagrams were developed to provide a comprehensive representation of both the structural organization and operational workflow of the proposed system.

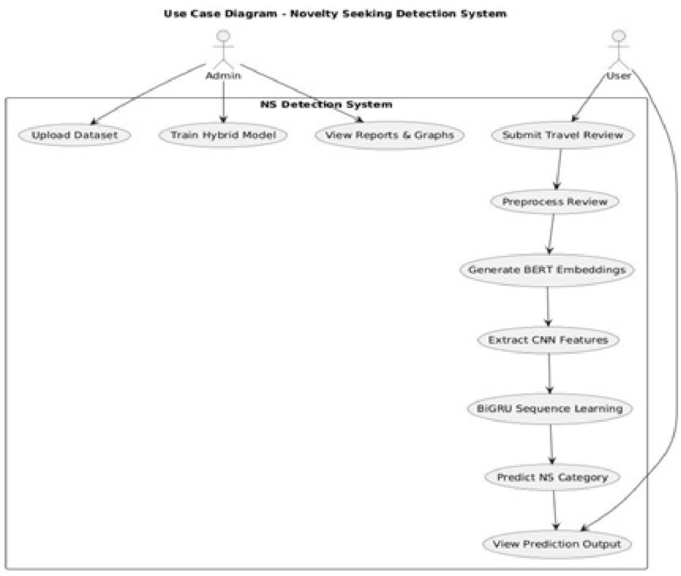

Fig-3.5.1: Use case diagram

The use case diagram complemented this structural view by outlining the overall prediction workflow, capturing interactions between the data source and the analytical framework from review input through preprocessing, feature extraction, model inference, and novelty-seeking classification output.

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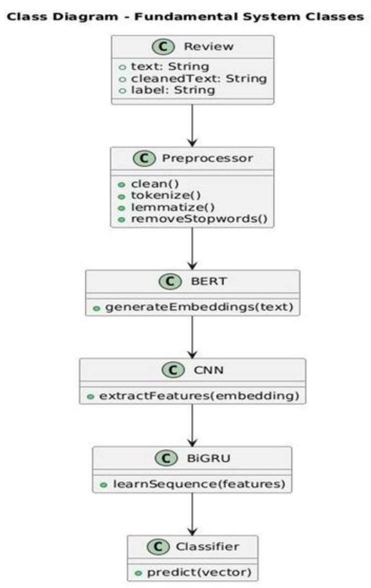

Fig-3.5.2: Class diagram

The class diagram described relationships among the principal components of the framework, including the Review Dataset, Preprocessing Module, Embedding Engine, Convolutional Network, Bidirectional Recurrent Layer, and Classification Module, thereby illustrating how data and functionality were distributed across the architecture.

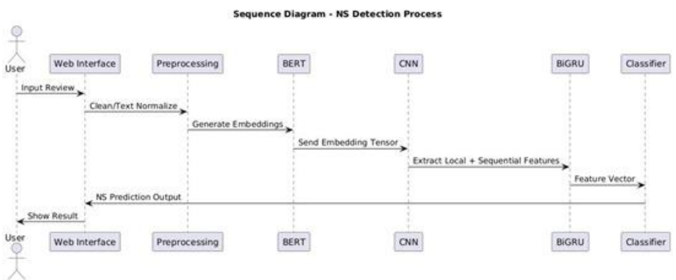

Fig-3.5.3: Sequence diagram

To further clarify system dynamics, a sequence diagram was constructed to depict the temporal progression of data as it traversed successive processing stages, beginning with preprocessing and continuing through embedding generation, convolutional analysis, recurrent encoding, and final classification.

3.6 Experimental Setup

The framework was implemented in a deep learning environment integrating transformer and neural network components. The dataset of 4,000 travel reviews was divided into training and validation sets. Key hyperparameters, including learning rate, batch size, kernel size, hidden units, and dropout, were empirically tuned through preliminary experiments. Training ran for multiple epochs until performance stabilized. Additional experiments varied parameters to evaluate scalability and generalization. During

training, loss curves, validation metrics, and computational latency wclosely monitored. This systematic setup ensured accurate performance assessment, reliable reproducibility, and a clear understanding of the novelty- seeking detection model under realistic experimental conditions in practice.

3.7 Model Processing Mechanism

The travel review data were processed using a hybrid deep learning pipeline that was designed to gradually convert raw textual content into novelty-seeking predictions. In the initial stage, each review was passed through preprocessing where normalization, tokenization, stop-word removal, and sequence standardization were carried out. This step was important because the collected reviews contained variations in writing style and informal expressions, which required cleaning before being used for model learning.

After preprocessing, the token sequences were provided to a contextual embedding layer based on a bidirectional transformer model. At this point, the model captured contextual meaning by considering surrounding words, allowing each token to be represented in a more informative

vector form. These embeddings were then supplied to a convolutional module, where filters were applied across the sequences to detect localized textual patterns that could indicate novelty-seeking behavior, such as mentions of unusual locations or distinctive activities. Activation and pooling operations were applied to retain prominent features while reducing dimensional complexity.

The embeddings obtained from the previous stage were then provided to a convolutional module to further analyze localized patterns within the review text. In practice, this stage helped highlight short phrases that appeared to reflect

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novelty-oriented experiences, including references to unfamiliar destinations or unique activities described by travelers. Convolutional filtering was applied across the embedding sequences, followed by activation and pooling operations that retained more informative signals while reducing overall representation size. This step contributed to emphasizing phrase-level characteristics in the reviews before sequential modeling was performed.

Finally, the learned representation was passed to a fully connected layer with sigmoid activation, which produced probability scores representing novelty-seeking behavior. These probabilities were converted into binary predictions using a predefined threshold. During training, binary cross-entropy loss was used to measure prediction error, and parameter updates were performed using the Adam optimizer to support stable learning. Overall, this processing mechanism enabled the model to progressively refine travel review text into structured representations that could support novelty-seeking classification.

3.8 Evaluation Parameters

The model was evaluated with the intention of understanding not only its prediction accuracy but also how it behaved during practical experimentation. Accuracy, precision, recall, and F1 score were examined throughout the experiments to see how reliably novelty-seeking instances were detected in the travel review data,
as looking at a single metric alone did not adequately reflect classification performance. While conducting the experiments, observations were also made regarding training duration and inference response, which provided a general sense of how efficiently the model operated. Attention was similarly given to memory consumption
and model size, since these aspects influenced resource usage during training and would affect future deployment considerations. To check whether performance remained stable, the model was run under different settings such as

changes in batch size, sequence length, and training epochs, allowing variations in behavior to be observed. Repeated experimental runs with adjusted hyperparameters were also carried out to confirm that the reported results represented consistent performance rather than behavior tied to a specific parameter configuration.

IV.RESULTS

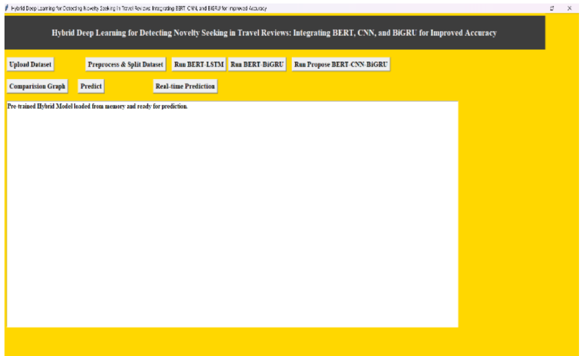

Fig. 4.1 Home page

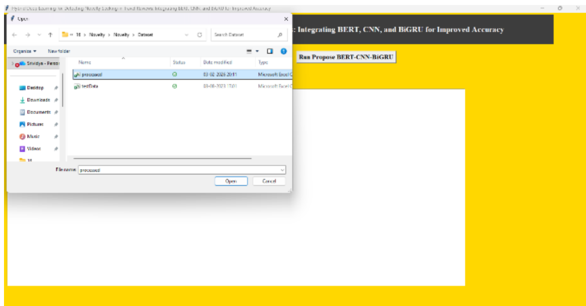

Fig.4.2 DataSet Upload page

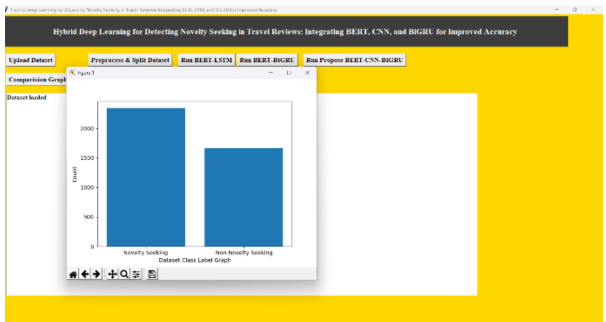

Fig. 4.3 Split DataSet Page

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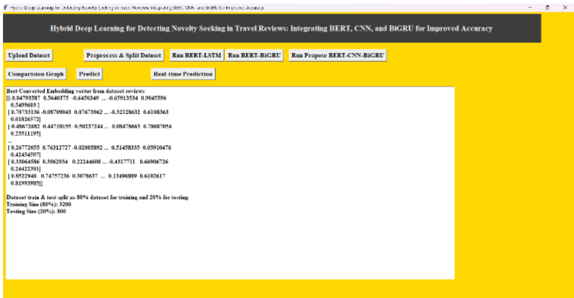

Fig.4.4 Preprocess Page

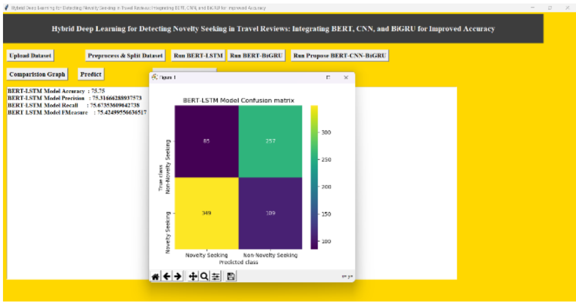

Fig.4.5 Confusion matrix(BERT-LSTM)

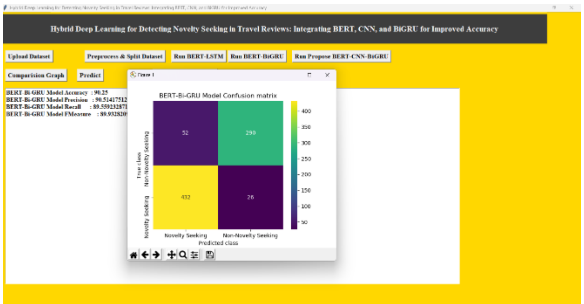

Fig.4.6 Confusion matrix(BERT-Bi-GRU)

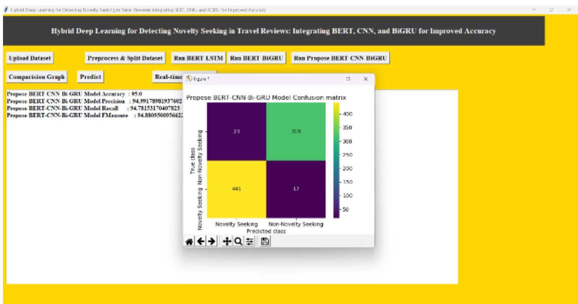

Fig.4.7 Confusion matrix(BERT-CNN-Bi-GRU)

V.RESULT ANALYSIS

5.1 Overview of Model Performance

We evaluated the new hybrid model BERT-CNN- BiGRU for detecting Novelty Seeking patterns in travel reviews using standard performance measurements such as Accuracy, Precision, Recall, and F1-Score to assess both the overall performance of the proposed hybrid model as well as the performance of the new model and the baseline models for detecting Novelty Seeking demographic identities and patterns.

Model	Accuracy
BERT–LSTM	75%
BERT–BiGRU	90%
Proposed BERT–CNN–BiGRU	95%

The proposed BERT-CNN-BiGRU model achieved an overall accuracy of 95%. This demonstrates that the current hybrid approach is performing significantly better than either of the two previous models. The improvements attributable to the three main building blocks of the hybrid model architecture are BERT providing context for the understanding of the text, CNN being used to extract critical phrases within a given document, and BiGRU providing an ability to remember sequence and flow within and between documents generating a deeper and more comprehensive understanding of the information contained in the text.

The results also indicate Precision, Recall, and F1-Score measurements are high and similarly balanced across all four types of Novelty Seeking behaviours providing evidence that no one type of behaviour is favoured over any other. Therefore, we can also infer that the BERT- CNN-BiGRU model will consistently identify all four types of Novelty Seeking behaviours.

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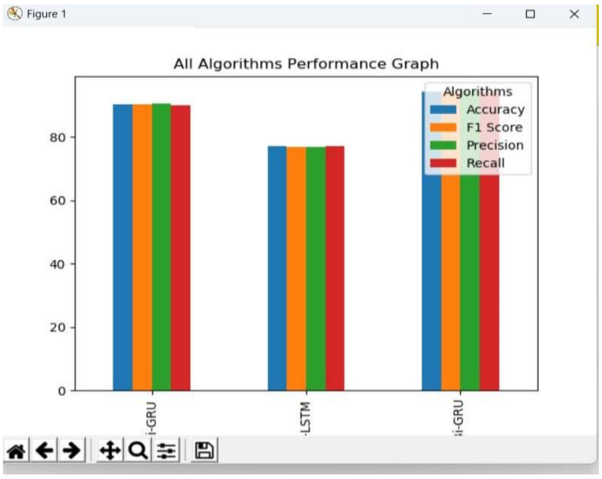

Fig.5.1.1: Comparison graph

5.2 Confusion matrix analysis

The confusion matrix of the proposed hybrid model provides a concise understanding of its classification behavior in identifying novelty-seeking patterns within travel reviews. The matrix shows that most reviews were correctly assigned to their respective categories, reflecting the model's strong capability to distinguish between exploratory and routine travel narratives. Reviews describing unique destinations, first-time experiences, and discovery-oriented activities were generally classified as novelty-seeking, indicating effective capture of behavioral semantics.

Similarly, a review focused on service quality, accomodation comfort, or general travel relief free from exploratory stress was correctly acknowledged as non-novelty. Limited misclassification occurs in situations where expressive language resembles novality cue or where novelty purpose is subtly expressed. Such cases, rather than the significant model restriction, emphasize the inherent ambiguity of the language of the original language. Overall, the confusion matrix demonstrates a balanced performance and reliable conduct bias which substantiates the suitability of the underlying base for the tourism assessment examination and recommendation applications.

VI.DISCUSSION

The present study analyses whether novelty-seeking behavior can be accurately detected from a travel review using a combined deep learning architecture. These findings suggest that the hybrid model provides a balanced and proficient
solution for performance categorization based on combination capture of contextual meaning, local textual form, and sequential dependency. The previous standalone approaches exhibit limitations either in deep contextual understanding or in model long-range bonds, while the proposed system overcomes the latter through architectural integration. The comparative assessment confirms the growing consensus that a hybrid deep acquiring knowledge model provides better forecasting capability than a single-model approach. The robustness of this approach is demonstrated by steady improvement in accuracy, precision, recall, and the F1 score. Still, the reliance on a single dataset restricts packed generalization over a sphere. Overall, the results suggest that hybrid deep learning models are highly suitable for scalable tourism analysis and progressive personalized recommendations.

VII.CONCLUSION

This study examines the use of an automated structure to detect novelty-seeking behaviour from the reviews of the travel experience using a hybrid deep learning technique. The previous standalone model showed a limitation in the capture of the intricate contextual and consecutive forms present in user-generated text. The proposed unified architecture effectively integrates contextual embeddings, convolutional feature extraction, and bidirectional sequential learning in order to increase classification efficiency. The experimental results, together with balanced accuracy and F1 score standards, show approximately 94% accuracy. The outline is scalable, robust, and suitable for analysing tourist information. Generally speaking, the research highlights the power of a hybrid deep acquiring knowledge model to enable personalized recommendation frameworks and data-driven tourism choice creation.

VIII.FUTURE WORK

While the proposed hybrid deep learning model effectively identifies novelty-seeking performance from travel reviews, there are still several avenues of improvement. Expanding the dataset to include larger and multilingual evaluation collections from various travel platforms could enhance the generalization of the model and facilitate cross-cultural evaluation. The outline may also be extended in order to create custom travel recommendation structures taking into account client tastes and travel history, enabling adaptive suggestions that share knowledge with discovery. In order to provide a wide range of perspectives, another promising route involves integrating multimodal information such as images, ratings, and location details. Moreover, future research could focus on improving computational productivity through lightweight model design and increased transparency using explanation- based Machine Learning strategies. The method can also be applied to a broader buyer deportation systematic analysis, including the e-commerce and support phases, where novelty-driven decision making involves a significant obligation. These additions underline the possibility of developing the proposed organization as a scalable and intelligent system for systematic analysis of the behaviour of humans.

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