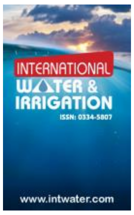

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Implementation Of Emotion Analysis Algorithm in Analysing Public Cognition of Industrial Heritage

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Abstract: Industrial heritage sites hold deep historical and cultural significance, yet public perceptions of their value vary widely. Visitors often form emotional connections to such sites, offering valuable insights for tourism enhancement and cultural preservation. Traditional methods fall short in effectively capturing public sentiment toward industrial heritage. To address this gap, we propose the Advanced Northern Goshawk-Responsive Generative Adversarial Network (ANG-RGAN) technique, which leverages emotion analysis to assess public sentiment. ANG-RGAN combines Responsive Generative Adversarial Networks with attention mechanisms, improving sentiment classification accuracy. Surveys and interviews conducted at Beijing's industrial heritage sites provided textual data for analysis. By employing tokenization, normalization, and term frequency-inverse document frequency (TF-IDF), emotional expressions such as curiosity, nostalgia, and melancholy were extracted and classified. Experimental results demonstrate superior performance, with an F1-score of 98.3%, accuracy of 98.9%, precision of 98.2%, and recall of 98.5%. Compared to existing methods, ANG-RGAN offers enhanced security and reliability in emotion-based assessments. This approach provides critical insights into public perceptions, fostering the growth of the tourism industry and the preservation of industrial heritage.

Keywords: Industrial Heritage, Emotion, Public Cognition, Advanced Northern Goshawk-Responsive generative adversarial network (ANG-RGAN)

1. Introduction

The frameworks of cultural conservation and urban planning, and the idea of industrial heritage serve as evidence that human civilization has developed and industry has impacted civilization. Treasures from the industrial era frequently act as moving recollections of a society's development toward modernization. But industrial heritage is not only about historical artifacts; it's also about public cognition and collective memory of the industrial era's influence on communities all over the globe [1].

1.1 Industrial Heritage

The tangible buildings, equipment, scenery, and intangible artifacts connected to industry are all included in the category of industrial heritage. The disaster, which can range from shuttered factories to active docks, provides physical reminders of history while narrating tales of labour, creativity, and social change [2]. Industrial heritage also refers to the cultural norms, stories, and customs that have developed in industrialized regions and have influenced the personalities and perceptions of place. Figure 1 shows the industrial heritage emotion.

Figure 1: Emotions Regarding Industrial Heritage visit

1.2 Preservation and Conservation

Due to the practical features of these structures and the rapid speed at which the approach is developing, defensive industrial heritage postures pose special problems. Emerging effectually and connecting people's cognition is vital for realizing a balance among the need for growth in the environment and upholding cultural sense [3]. The protectional include safeguarding the information and emotions connected with these places for the following generations, in addition to upholding the actual buildings.

1.3 Tourism and Economic Development

The meaning of industrial heritage possessions for travel and growth in the economy is cumulative. Communities can employ their historical capitals to generate travellers and encourage their communities by changing obsolete industrial services into museums, cultural centres, or mixed-use complexes [4]. To prevent the real labour and conflict histories embedded in these places from being misplaced, the commercialization of industrial heritage wants to be performed correctly.

1.4 Navigating Industrial Heritage Challenges and Opportunities

The method that the universal public perception assesses industrial heritage disturbs society and observes the past, present, and future. Some perceive these artifacts as nostalgic reflections of a modern era of wealth, while others see them as symbols of environmental destruction and oppression. It is essential to reconcile various perspectives to promote inclusive discourse. The preservation of industrial sites is threatened by issues, including urbanization and economic pressures, even if their significance is acknowledged. However, these difficulties also present chances for conservation strategies such as digitization and adapted reuse [5]. An Advanced Northern Goshawk-Responsive Generative Adversarial Network (ANG-RGAN) method to evaluate public cognition of industrial heritage employing an emotion analysis algorithm

The organization of the article is listed as follows. Section 2 explores the literature survey for public cognition of industrial heritage, section 3 represents the material and methods, section 4 indicates the experimental findings along with the discussion, and section 5 shows the conclusion and future direction of the article.

2. Literature Survey

Using web data crawling techniques and a Python data analysis package [11], information gathered from the 'mango' online tourism community were analysed, demonstrating a range of effects on visitor satisfaction related to the image of the destination, cognitive themes, and emotional experiences. By measuring visitors' brain reactions with electroencephalography (EEG), [12] attempted to determine the cognitive and affective effects of virtual cultural assets on travellers. They indicated that these kinds of encounters were well received. The approaches for potential development by contrasting the stewardship of the industrial past [13]. To determine cutting-edge techniques and fresh approaches, it examined financing, managerial, and legal frameworks. To facilitate the creation of design concepts that would improve the sustainability of historical tourism situations, [14] employed a space syntax-based technique to comprehend visitors' perception of space in heritage blocks of traditional historic neighbourhoods' emphasize conflicting public perceptions and support human-centric digitization techniques, statistical techniques, and multidisciplinary methodologies [15] to explore how society perceives artificial intelligence's (AI) significance in digitizing cultural material within the setting.

With an emphasis on natural heritage assets, [16] explored the sustainable growth of heritage tourism through the use of big data and AI-driven smart tourism technologies. The findings point to a well-balanced tourist environment and emphasized that integrating technology could promote environmentally friendly travel habits. Study [17] using real-world data created a conceptual structure to comprehend those locals' views of tourism growth and sentimental friendship affect their engagement in value-sharing behaviours within environments of intangible cultural heritage (ICH) tourism. The findings emphasized the significance of appearance and psychological cooperation. The emotional reactions, cognitive assessments, and coping mechanisms of locals in dark tourism destinations after the Canterbury earthquakes were investigated in [18]. The inhabitants evaluate these events according to their centrality and controllability, which frequently elicits unfavourable feelings like melancholy. Seeking solace and adopting a positive outlook were examples of coping mechanisms. Following a tragedy, dark tourism excursions can be utilized as a coping strategy. A structural equation model (SEM) [19] examined in formation through 588 visitors to examine how environmentally conscious tourists' cloud be when visiting cultural heritage sites. The results show that such conduct was favourably influenced by cognitive, emotional, and cultural experiences; cultural attachment played a role in modulating the connection. They offered theoretical understandings and useful recommendations for promoting the growth of sustainable tourism in locations with a rich cultural history. A cognitive appraisal theory-based model [20] examined the influence of legitimacy in historic tourism on visitors' desire to revisit. With attachment to places and lasting memories, reliability in several ways influenced revisit intention, based on data gathered from 596 participants at the Dujiangyan irrigation system. The information enriched understanding and offered theoretical perspectives for the growth of cultural tourism.

3. Proposed Methodology

The effectiveness of industrial heritage training is critical for improving people's emotions and performance. The suggested methodology's flow is shown in Figure 2. The industrial heritage emotion data was first collected for study and the dataset wasp reprocessed using the industrial heritage processed method. Next, we use TF-IDF for industrial heritage emotion feature extraction. The suggested ANG-RGAN was utilized in the study to categorize industrial heritage training.

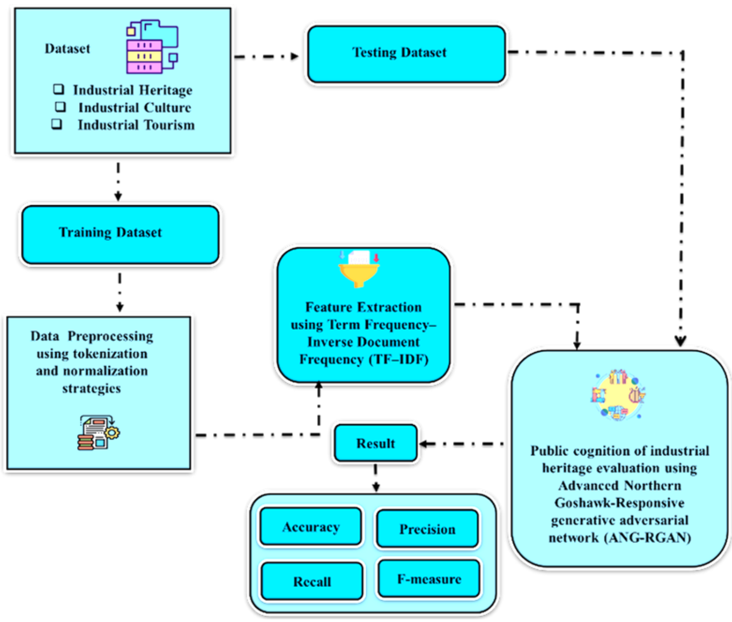


Figure 2: Overall Structure of Proposed Methodology

3.1 Data Collection

In an article on industrial heritage, industrial culture, or industrial tourism, emotion reviews from 1014 participants were analysed to understand their sentiments towards different locations. The data set is divided into two sets, the training set (70%) and the testing set (30%), revealing a spectrum of emotions like fascination, intrigue, sadness, happiness, and nostalgia. Participants visiting these sites often expressed a mix of emotions: some felt sad, witnessing the decay of historical structures, while others were happy and impressed by the preservation efforts and the opportunity to learn about industrial history. The training phase focused on identifying patterns in these emotional responses, while the testing phase validated the model's ability to predict sentiments accurately. The research emphasized the complicated emotional environment associated with industrial heritage, focusing on its cultural preservation and tourism experiences.

3.2 Data Preprocessing

Textual information from surveys, interviews, and social media platforms must be cleaned and arranged to be prepared for emotion evaluation, containing tokenization and normalization. This strategy is known as preprocessing for the public perception of industrial heritage.

3.2.1 *Tokenization*

The most crucial and commonly employed text preparation strategy is tokenization. It is employed for splitting up an input text into smaller components. The tokens, which might be words, phrases, or symbols, each depictsignificantcharacters of the input text and are crucial to several natural language processing (NLP) tasks, contain emotional evaluation, text analysis, computerized translation, and processing of text are frequently provided during the initial stages, and they include all of the input text in all of their formats. Text tokenization is a procedure that operates at several separate textual levels, with a word or phrase stage being the most common. The raw text data is a broad strategy separated into discrete units known as words at the lexical level; each word is symbolized by a separate token.

3.2.2 *Normalization*

The crucial phase in the background of the information is normalization. To safeguard correct results and characteristics that are secure within a certain variety, the normalization process'sobjective is to scale and alternate the raw input features. Often, the range is labeled as having a difference between 0 and 1.An average of 0 for the raw characteristic and a standard variance of 1. During the strategy training phase, normalization is generally significant since it enhances the quality of every raw input of informationand ensures that it contributes positively. It aims to fasten up the convergence procedure during the training of the framework while decreasing the range of higher scale of all characteristics in the learning procedure of AIstrategies. In the preprocessing stage, raw information undergoes cleaning, normalization, and tokenization to ensure consistency and quality.

3.3 Feature Extraction

During feature extraction, relevant characteristics and patterns are identified and extracted from the treated information to prepare for subsequent evaluation or modeling tasks. For the most famous and well-known weighting measures in research, we chose the Term Frequency–Inverse Document Frequency (TF–IDF) for the feature extraction strategy. An indicator of a word's significance within a corpus is the TF-IDF. The measurement is calculated from the product of inverse document frequency and word frequency. The several times a word occurs in a document is called its term w, and the meaning of the inverse document frequency is expressed in equation (1):

$$idf(W) = log\left(\frac{|D|}{\{d_i: s\varepsilon d_i\}}\right) \qquad (1)$$

The quantity of documents in the dataset is represented by $D|$, and the number of records containing the word w is shown by $\{d_i: s\varepsilon d_i\}$. Equation (2) offers the $sfidf$ value of a word w.

$$sfidf(w) = sf(w). idf(w) \qquad (2)$$

By allocating weights to the words based on their frequency throughout the corpus and their frequency in a document, TF-IDF effectively extracts features. This promotes crucial words and documents the impact of common ones, enabling more accurate textual information categorization and assessment. The collected characteristics are then sent into the ANG-RGAN approach that has been recommended for additional analysis.

3.4 Emotion Algorithm using Advanced Northern Goshawk-Responsive Generative Adversarial Network (ANG-RGAN)

The ANG-RGAN to the specific emotional evaluation of industrial heritage locations, employing to validate and analyse visitor emotions with high fidelity and accuracy.

➢ **Responsive generative adversarial network (RGAN)**

A set of artificial intelligence systems that were created to produce industrial legacy synthesizing sentimental data by using a discriminator and a generator to create two artificial neural networks connected. Gans might be used in an AI-assisted environment to support and enhance psychological ties to former factories. High-fidelity experiments of visitors' feelings and encounters with these cultural places may be produced using RGANs, which are capable of expressing subtleties like interest, remembrance, and sorrow. Figure 3 represents the architecture of RGAN.

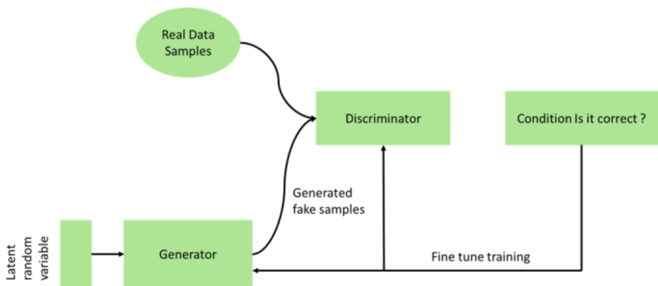
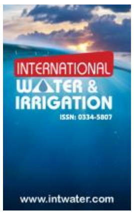


Figure 3: Architecture of RGAN model



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The strategy enhances the understanding of emotional patterns and perceptions connected with industrial heritage, thereby enhancing the interpretation and preservation techniques for these culturally significant sites. To enhance the technique's capacity to identify and classify industrial heritage influenced by emotional elements, the generator network creates artificial information that mimics real inputs, while the discriminator network evaluates to create data's veracity. By adding industrial heritage emotion data with this synthetic data, training strategies developed to identify and classify industrial heritage will have a stronger foundation. RGANs improve the variety and volume of training data, which increases the accuracy and dependability of models. As a result, these models get better at predicting individual heritage brought by emotional change, which makes early detection and more effective response tactics possible. This use of RGANs demonstrates that challenging environmental issues can be addressed with innovative data-generating methods, first proposed as a collection of flexible methods for generative model learning. RGAN consists of two deep-learning neural networks (a generator $H$and and a discriminator C). The networks are trained by using the optimization function in a two-player game called min-max represented in equation (3).

$$\underset{H}{min}\underset{C}{max} U(C,H) = F_{w\sim O_{real}}[logC(w)] + F_{y\sim o_y}(y)[\log\left(1 - C\left(H(y)\right)\right)] \quad (3)$$

Where$y$initiated from an arbitrary noise distribution as the data generator.o_y (Typically, the uniform distribution) was the actual data derived from the actual distribution of data O_{real}. The generative model H and the discriminative model Ctraining concurrently with competing goals is done inside RGAN. It isthe first objective to train a generative network to change the noise vector y from the data distribution $o_y$into the sample $H(y)$. To get to this place, H must get previous information from the actual distribution of data O_{real}then uses the information in the process of creating emotion samples. The output samples obtained from $H$are fed intoC, its objective is to accurately differentiate the produced emotion sample from actual data. When the created emotion sample is categorized as genuine or fraudulent during the training phase, the generator will perform better the following time. The generation of emotional data on industrial historical buildings through the use of RGANs, these datasets must next be optimized through the application of sophisticated NGO optimization techniques. Through the NGO approach, the emotional representations, the analysis's accuracy and depth about visitor attitudes towards historical industrial surroundings are improved.

- **Advanced Northern Goshawk Optimization (ANGO)**

Using emotional evaluation to analyse Industrial Heritage, the ANGO method could be used efficiently. It is modelled after the hunting habits of the Northern Goshawk bird. This metaheuristic approach emphasizes the stages of exploration and exploitation to identify the best solutions, imitating the bird's strategic hunting methods. ANGO could be used to optimize sentiment detection models in the environment of emotion evaluation at industrial heritage locations by actively modifying parameters to capture the complex emotional reactions of visitors. Figure 4 shows the process of the ANGO method.

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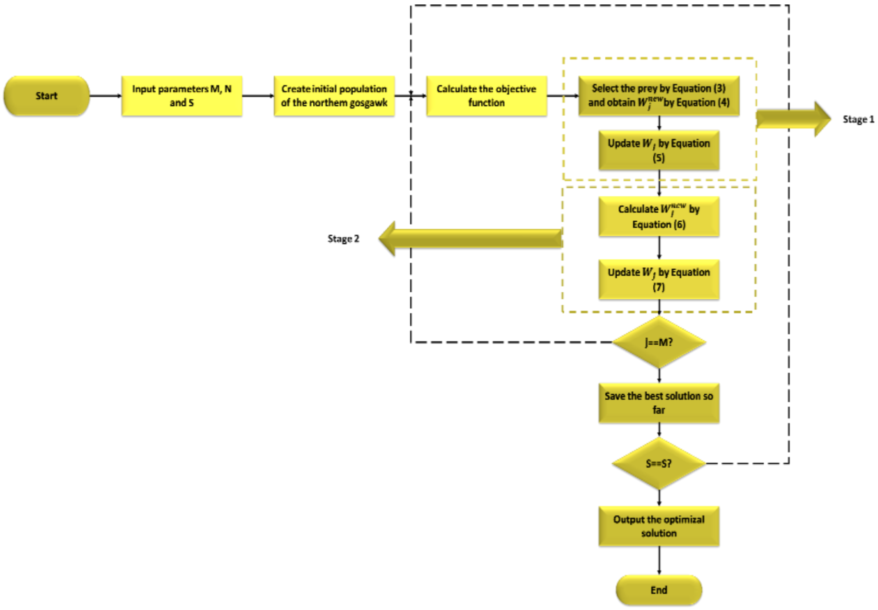

Figure 4: Process of ANGO method

The northern goshawk's population size as well as location may be expressed using equation (4), these population matrices are in the ANGO method:

$$W = \begin{bmatrix} W_1 \\ \vdots \\ W_j \\ \vdots \\ W_M \end{bmatrix} = \begin{bmatrix} w_{1,1} & \cdots & w_{1,i} & \cdots & w_{1,n} \\ \vdots & \ddots & \vdots & \vdots & \\ w_{j,1} & \cdots & w_{j,i} & \cdots & w_{j,i} \\ \vdots & \vdots & \ddots & \vdots & \\ w_{M,1} & \cdots & w_{M,i} & \cdots & w_{M,n} \end{bmatrix}_{n\times M} \quad (4)$$

The northern eagle population's objective function quantity in the ANGO algorithms is expressed in equation (5) as a vector.

$$E = \begin{bmatrix} E_1 \\ \vdots \\ E_j \\ \vdots \\ E_M \end{bmatrix}_{1\times M} = \begin{bmatrix} E(W_1) \\ \vdots \\ E(W_j) \\ \vdots \\ E(W_M) \end{bmatrix}_{1\times M} \quad (5)$$

The preceding computational equations (6), (7), and (8) represent the northern goshawk's aggressive behavior and prey choice during its initial phase.

$$P_j = W_l \quad (6)$$

$$w_{j,i}^{new,O1} = \begin{cases} w_{j,i} + q\left(p_{ji} - J w_{j,i}\right), E_{oj} < E_j \\ w_{j,i} + q\left(w_{j,i} - p_{j,i}\right), E_{oj} \geq E_j \end{cases} \quad (7)$$

$$W_j = \begin{cases} W_j^{new,O1}, E_j^{new,O1} < E_j \\ W_j, E_j^{new,O1} \geq E_j \end{cases} \quad (8)$$

Where t is an arbitrary number in the interval $[1, N]$, P_j is the prey location, and E_{o_j} is the objective function value of p_j. $w_{j,i}^{new,O1}$is the new location of the j^{th} northern goshawk's i^{th} scale, $E_j^{new,O1}$ newinitial stage of the j^{th}northern goshawk's objective function level. The $q$is a member of $[0, 1]$. The subsequent algebraic equations (9) to (11) represent prey escape and the northern goshawk pursuing prey in their subsequent stage:

$$W_{j,i}^{new,P2} = w_{j,i} + Q(2r-1)w_{j,i} \quad (9)$$

$$W_j = \begin{cases} W_j^{new,P2}, E_j^{new,P2} < E_j \\ W_j, E_j^{new,P2} \geq E_j \end{cases} \quad (10)$$

$$Q = 0.02\left(1 - \frac{s}{S}\right) \quad (11)$$

Where the greatest repetition frequency Q and s is the present repetition number. The predicting responsibilities are much improved after using the ANG-RGAN approach for industrial heritage based on emotion evaluation. The RGANs capture ranging from desire to serious consideration, simulating a wide variety of emotional reactions that visitors might experience at industrial historical sites. The ANGO algorithms perform to efficiently comprehend and forecast these emotional patterns by optimizing parameters and methods.

4. Experimental Findings

This section utilizes Python 3.11 to develop novel algorithms on a Windows 10 laptop. The accuracy, precision, and recall performance measures for the ANG-RGAN approach for the five emotions like fascination, intrigue, sadness, happiness, and nostalgia are displayed in Figure5. Happy has the highest accuracy rate (97%), while Fascination has the lowest (86%).

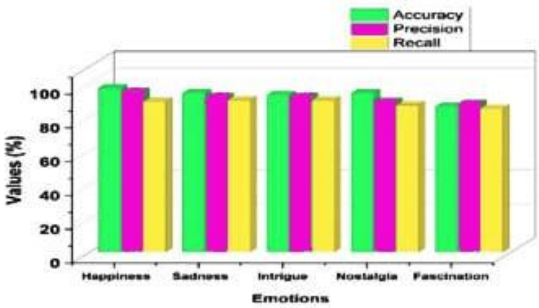

Figure 5: Emotion Analysis Using ANG-RGAN Strategy

4.1 Performance Evaluation

The effectiveness of an AND-RGAN method is contrasted with those of modern techniques including the Backward Group Relevance Optimization Convolutional Neural Network (BGRO-CNN), Attention-Based Long Short-Term Memory (LSTM) Convolutional Neural Network + Term Frequency-Inverse Document Frequency (ABLCNN+FFIDF), and Improved Sparse Principal Component Analysis – Long Short-Term Memory (ISPCA-LSTM) [16] as well as measures including accuracy, precision, recall, F1-score.

➢ **Accuracy**

Accuracy uses emotion analysis to inform public's perception of industrial heritage.The percentage of properly classified public perception about industrial legacy relative to the total number of opinions is examined. The equation (12) allows for its quantification.

$$Accuracy = \frac{\text{Number of correctly predicted emotional responses}}{Totalnumberofemotionalresponse} \times 100\% \quad (12)$$

Table 1: Outcomes Of Accuracy

Methods	Accuracy (%)
BGRO-CNN [16]	95.2
ABLCNN+FFIDF [16]	95.2
ISPCA-LSTM [16]	97.4
ANG-RGAN [Proposed]	98.9

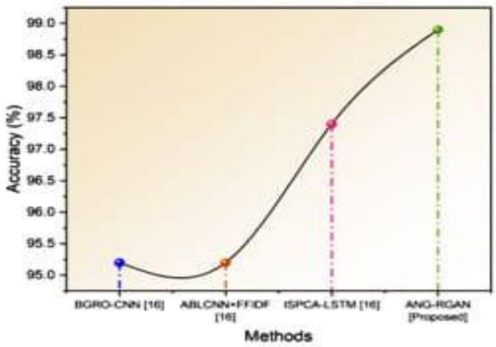

Figure 6: Graphical Representation of Accuracy

Table 1 and Figure 6 show the graphical representation of accuracy. The proposed ANG-RGAN outperformed the prior technique achieving the highest accuracy of 98.9%. The accuracy compared to the established methods, such as BGRO-CNN attained 95.2%, ABLCNN+FFIDF attained 95.2%, and ISPCA-LSTM attained 97.4%.

➢ **Precision**

Emotional reality tourism is a comprehensive cultural heritage experience that simulates people's emotions generated by cultural heritage environments. It makes it easier to discover emotions in a variety of locations by integrating modern technology. An indicator of precision in emotional realism in tourist activity is found in perceptual reproductions and user participation (equation (13)).

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{13}$$

Table 2: Outcomes Of Precision

Methods	**Precision (%)**
BGRO-CNN [16]	94.3
ABLCNN+FFIDF [16]	94.1
ISPCA-LSTM [16]	97.9
ANG-RGAN [Proposed]	98.2

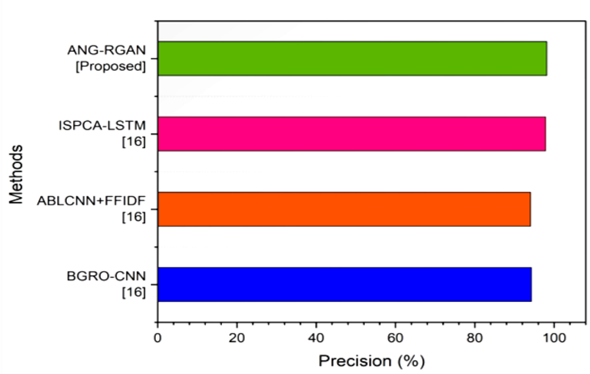

Figure 7: Result of Precision

Table 2 and Figure 7 show the results of precision. The proposed ANG-RGAN exceeds the conventional strategies, achieving the highest precision of 98.2%. The precision of the conventional techniques, such as BGRO-CNN achieved 94.3%, ABLCNN+FFIDFachieved 94.1%, and ISPCA-LSTM achieved 97.9%.

➢ **Recall**

Recall in the setting of historical heritage is a gauge of the way pertinent events are captured in the digital realm, indicating that all relevant aspects of a location are represented. The public's emotions and comprehension of industrial heritage are retrieved and examined using an emotion analysis, which is referred to as recall. It includes the practice of using emotion analysis tools to access and understand the public's collective cognitive reactions to industrial history. The ratio of positive emotions to the overall amount of fascination, intrigue, sadness, happiness, and nostalgia events is represented by equation (14).

$$\text{Recall} = \frac{\text{TP}}{\text{TP+False Negative (FN)}} \times 100 \tag{14}$$

Table 3: Outcomes of Recall

Methods	Recall (%)
BGRO-CNN [16]	94.5
ABLCNN+FFIDF [16]	94.9
ISPCA-LSTM [16]	97.2
ANG-RGAN [Proposed]	98.5

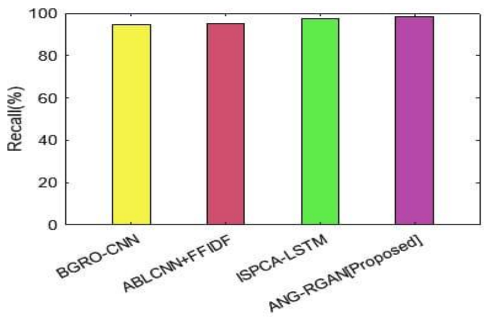

Figure 8: Comparison of Recall

Table 3 and Figure 8 show the results of recall. The proposed ANG-RGAN outperformed the prior techniques, achieving the highest recall of 98.5%. The recall of the established methods, such as BGRO-CNN performed at 94.5%, ABLCNN+FFIDF performed at 94.9%, and ISPCA-LSTM performed at 97.2%.

➢ **F1-score**

The F1-score examining that the public perceives industrial history via the use of emotion analysis algorithms. It measures how well the public's emotional responses linked to industrial heritage are identified and categorized by the emotion analysis algorithm. A more balanced assessment of a simulated tourist experience's accuracy and completeness could be made using the F1-score, which is the harmonized way to evaluate recall and precision. The F1-score equation (15) is,

$$\text{F1} - \text{score} = \frac{2\times\text{precision} \times\text{recall}}{\text{precision+recall}} \tag{15}$$

Table 4: Comparison outcome of F1-score

Methods	F1-Score (%)
BGRO-CNN [16]	94.4
ABLCNN+FFIDF [16]	94.5
ISPCA-LSTM [16]	97.5
ANG-RGAN [Proposed]	98.3

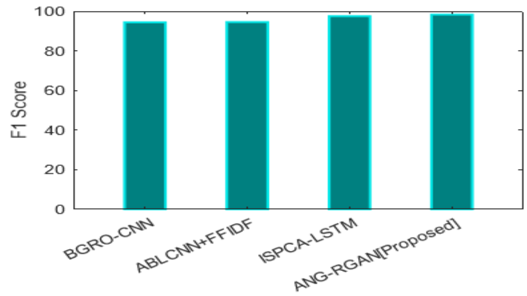

Figure 9: Comparison of F1-score

Table 4 and Figure 9 show the results of the F1-score. The proposed ANG-RGAN exceeds the traditional approaches, achieving the highest f1-score of 98.3%. The f1-score of the traditional techniques, such as BGRO-CNNachieved 94.4%, ABLCNN+FFIDF achieved 94.5%, and ISPCA-LSTM achieved97.5%.

4.2 Discussion

Industrial heritage sites depict crucial connections to the industrial past, and public perception and appreciation of these sites vary widely. The visitors emotionally engage with industrial heritage and can inform techniques to improve cultural preservation and tourism experiences. The conventional method faces some limitations. BGRO-CNN [15] has several drawbacks, with the prospect of the greatest computational and time needs for training and hyper-parameter adjusting. In situations when quick model iteration or operation is required, this might make it less practical. ABLCNN+TFIDF [16] has a few drawbacks, together with the potential need for large computing resources and knowledge for effective optimization due to the complexity of hyperparameter tuning resulting from the integration of two separate algorithms. Comparing ISPCA-LSTM [16] to simpler algorithms, the disadvantage is the latter's higher processing demand and complexity. ISPCA-LSTM pertinence in applications where effectiveness and rapid creation are hazards can be limited by the additional knowledge and computing resources required for its implementation and optimization. With the use of an efficient training process with simple hyperparameter substitutes the ANG-RGAN strategies to catch these problems. Because it improves deployment ease and diminished computing supplies, it is more suitable for applications that are essential to be deployed rapidly in situations with limited resources.

5. Conclusion

This research employed an emotion evaluation algorithm to create the Advance Northern Goshawk-Responsive Generative Adversarial Network (ANG-RGAN) strategy as an influence to understand public emotions like fascination, intrigue, sadness, happiness, and nostalgia of industrial heritage location. Fascination, nostalgia, melancholy, pleasure, and pride were among the emotions that were investigated by collecting information via surveys with visitors. With the combination of RGAN structure and modification procedure, the ANG-RGAN strategy represents outstanding performance indicators in emotional evaluation (accuracy 98.9%, precision 98.2%, recall 98.5%, and f1-score 98.3%). This methodology provides a thorough evaluation of the emotion connected to experiences associated with industrial heritage, which is a significant progress toward conventional methodology. The obligation for large-scale information for more comprehensive generalization and possible opinions in visitor replies are constraints. To enhance sentiment evaluation, future studies should examine real-time emotional assessment strategies and combine multimodal sources of information. The ANG-RGAN strategy offered insightful data on public perception that is significant for enhancing cultural preservation strategies and authorizing the growth of the tourist sector through holistic heritage experiences.

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