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Artificial Intelligence-Driven Smart Scenic Management: Automated Decision Making and Optimization

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Abstract: With the continuous progress of technology and economic development, the overall quality of human life has witnessed significant enhancements. Smart tourism, leveraging information technology, plays a crucial role in integrating tourism resources to offer tailored travel solutions for visitors. This approach ensures that tourists can access convenient services, such as traffic inquiries, browsing information about tourist scenic spots, and efficient route planning. As the representation of tourist information increasingly relies on visual content, particularly images, rather than textual descriptions, a challenge arises for tourists who wish to explore further details about attractions depicted in pictures. To address this issue and elevate the overall tourist experience, this study proposes an artificial intelligence-driven smart scenic management model. The model employs the modified golden jackal optimization (MGJO) algorithm for feature extraction and optimization, aiming to select the most optimal features from pool of possibilities. Additionally, the deep multi-layer recurrent neural network (DM-RNN) is utilized for the detection of tourist scenic spots, enhancing detection accuracy. A dataset of tourist-friendly scenic spots in Hsinchu City, Taiwan, is used as an example to demonstrate the effectiveness of the proposed model. The executed vacationer beautiful spot acknowledgment model effectively distinguishes 28 places of interest in Hsinchu. The experimental results demonstrate that the model that makes use of DM-RNN is both effective and precise. In terms of accuracy and mean average precision, the model performs better than previous cutting-edge models.

Keywords: *smart scenic management; tourist scenic spot; artificial intelligence; automated decision making; feature optimization*

1. INTRODUCTION

With the coming of the monetary time, the interest level of the travel industry buyers is bit by bit moving from the degree of involvement scattering to the degree of undifferentiated that everybody can partake in a similar travel experience similarly [1]. Unique emotions are the highlight of the experience economy. According to this point of view, the travel industry is a significant way for individuals to look for curiosity, distinction, miracle, magnificence, and information [2]. The customary method of mass travel disregards the cooperation with the travel industry shoppers, so it can't furnish the travel industry purchasers with a remarkable and separated insight. The contradiction between popularized and standardized services is overcome by smart tourism [3]. That is, while fulfilling the travelers to partake in similar experience items, it can likewise fulfill the customized experience impact of the vacationers. With the increment of metropolitan populace, individuals' reasoning has additionally changed [4]. As well as meeting the essential living necessities of dress, food, lodging and transportation, individuals have started to have more prerequisites for the travel industry, get-away, diversion, and different viewpoints. In any case, the scourge significantly affects the travel industry in the beyond two years, and conventional travel strategies are as of now not appropriate [5].

Smart scenic management revolutionizes how tourists protect, maintain, and enjoy nature [6]. Smart scenic management employs new technology, notably AI, to optimize natural settings and give visitors a pleasant and immersive experience. The holistic approach covers eco-tourism, environmental conservation, and technology [7]. The ever-changing tourism industry requires strategic landscape management. Balancing tourism operations and protecting the environment is crucial. As outdoor activities become more popular, this balance is more important. Smart scenic management monitors, evaluates, and improves scenic areas with cutting-edge

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technology [8]. The regulations cover resource utilization, tourism, and the impact on the environment. Beyond conservation, smart scenic management uses data, constant monitoring, and predictive modeling to make decisions. Artificial intelligence can help scenic region managers understand tourist behavior, natural dynamics, and climate [9]-[12]. They can develop anticipatory management techniques to reduce risks and increase sustainability. Conventional scenic area management is arduous, inefficient, and reactive. The lack of data and analytics worries scenic managers. These tools are essential for management planning. Managers need immediate information on tourist traffic, the environment, and resource utilization to balance safeguarding the environment and visitor experiences [13]. Another challenge is that beautiful settings are complex and ever-changing. Due to shifting weather, seasonality, and biology, managers struggle to predict and respond to new environmental hazards and opportunities [14]. Because natural landscapes are vulnerable the managers find it difficult to apply management approaches. Tourism pressures traditional scenic management measures.

Traditional administration is inefficient and slows decision-making also, these methods are demanding and manual [15]. Limited funds and people may make emergency prevention and response difficult for scenic managers. Scenic areas may lose their long-term viability, harming ecological systems and visitor experiences. Data analysis, pattern detection, and decision assistance in scenic management have been transformed by artificial intelligence (AI) [16]. In no other time have such capabilities existed. Scenic managers use AI to examine massive camera, and surveillance data. AI algorithms enable this. These data let management analyze visitor behavior, identify patterns, and predict future issues and opportunities [17]. This management software optimizes resource allocation and automates tiresome tasks. This is crucial to AI-driven scenic management. AI systems can detect connections, trends, and irregularities in vast statistics that people miss. AI-powered predictive analytics may help scenic managers' spot future hazards [18]. This permits proactive management to reduce risks before they escalate. AI systems can identify peak tourism seasons and erosion-prone places using weather forecasts, visitor profiles, and prior data. This involves finding habitat-damaging locations. AI based machine learning and deep learning models can enhance visitor experiences with tailored recommendations, immersive displays, and complete virtual tours [19][20].

Our contributions. We propose an AI driven smart scenic management model which analyzes the picture carefully to detect tourist scenic spot. The significant commitments of proposed work are given as follows.

1. A significant advancement in the processes of feature extraction and optimization can be traced back to the introduction of the modified golden jackal optimization (MGJO) algorithm. This calculation is explicitly intended to explore through various highlights and select the most ideal ones. The model uses the MGJO algorithm to improve its ability to identify and prioritize relevant features, which improves the system's overall efficiency and effectiveness.
2. The joining of the deep multi-layer recurrent neural network (DM-RNN) further hoists the model's capacities in identifying traveler grand spots. This profound learning engineering is known for its capacity to catch complex fleeting conditions, which is especially worthwhile in picture examination errands. By utilizing DM-RNN, the model accomplishes further developed discovery exactness, guaranteeing a more exact recognizable proof of vacation destinations inside pictures.
3. Using a real-world dataset of tourist attractions in Hsinchu City, Taiwan, the proposed model's viability and performance are demonstrated. When applied to this dataset, the model successfully identifies 28 popular tourist destinations in Hsinchu. This exact confirmation shows the functional pertinence and viability of the proposed model in a true setting.

The remainder of this paper is coordinated as follows: Segment 2 explored the different models for vacationer grand spot acknowledgment utilizing profound learning. The problem description and the detailed working process of proposed AI driven smart scenic management model is explained in Section 3. Section 4 examines the effectiveness of the proposed and existing smart scenic management model using results and comparative analysis. Finally, the paper concludes in Section 5.

2. RELATED WORKS

2.1 State-of-art study on tourist scenic spot recognition models

Li et al. [21] proposed an unsupervised intelligent management platform for Bed and Breakfast enterprises uses data mining and a crawler program to examine the data. The system allows unattended management using wireless RFID technology, improving operational efficiency. RFID detection system uses linear SVM learning method to achieve 99.25% accuracy, proving its applicability and reliability. This unique solution supports the national aim to revitalize rural communities through intelligent services by providing high-quality, energy-efficient services. The unsupervised intelligent management system advances the hospitality sector and rural sustainable development by helping merchants make educated decisions and streamline operations.

Wang et al. [22] introduced an AI framework that automatically identifies tourism photos, advancing the tourism industry's automation. The framework runs without human intervention using transfer learning and deep learning, demonstrating the promise for smarter, more efficient tourism. Using internet destination photographs from Australia, the study shows that a model integrating advanced convolutional neural networks and mixed transfer learning improves image identification. The framework establishes the groundwork for tourism computer vision research by identifying 25 picture classification categories representing tourism scenarios. The study also advances online destination image analysis and big data research in tourism with an intelligent automation framework, providing significant insights for smart destination marketing and management. The suggested framework provides a cutting-edge data mining method that could transform tourism destination management and marketing.

Zhang et al. [23] examine how AI is used in travel and tourism, including personalization, recommendation systems, robots, predictive analytics and conversational interfaces. The study emphasizes the growing importance of cyber security in the sector by emphasizing AI's role in improving travel experiences and information security. An intelligent comprehensive tourism cloud platform is shown to demonstrate the complex system architecture and integration of databases needed to aggregate provincial tourism resources into a single information-sharing ecosystem. The study predicts a transformation in tourism management techniques using big data-driven decision-support systems to improve problem-solving and service quality. By modeling tourism service scenarios, the research shows how AI and big data analytics increase decision accuracy and build the framework for sustainable tourism development.

Yang et al. [24] examine the gradual but inevitable rise of AI and the necessity to understand its profound impact on human society. AI's ability to educate, train, and assist humans could boost production in food, medical care, schooling, and energy services. The study also warns that algorithmic bias and governance issues might undermine human rights and exacerbate gender, race, and employment inequality. In picturing a future with human-centered AI with stresses human viewpoints, understanding the complex relationship between AI technology and human realities. The study promotes multidisciplinary conversations between technology and humanity-based academics to better understand HAI and its many social impacts, pushing for a more inclusive and informed AI development and deployment.

Wang et al. [25] examines the early use of AI in the production of sports news. recognize the early stages of AI integration in news production and investigate innovative sports news dissemination models within the context of wireless communication networks and AI breakthroughs. The study examines wireless network interaction and AI algorithms to determine their impact on sports news distribution production innovation, particularly neural network algorithms. Due to rising sports interest and changing news consumption, news dissemination methods are being updated to keep up. Rapid advances in AI and wireless communication have enabled new news transmission methods that surpass traditional ones. Thus, researchers as well as professionals are building new sports news production models using wireless network connection and AI technologies. This practical challenge addresses customers' changing needs and emphasizes the necessity of news media technology.

Currie et al. [26] mentioned financial markets require government regulation to promote stability and justice due to fragmentation of the market, technical intricacy, and information asymmetry. This study uses Simon's theory of limited rationality to examine how governments create and implement automated trading regulations. Research on primary and secondary data shows four phases of evolutionary technological development in financial markets, each posing new problems for regulators in managing systemic and company-specific risks. As regulators manage bounded rationality and restricted optimization to avoid financial market risks, they favor satisfying solutions over optimal ones. Regulatory judgments prioritize ex-post criteria over ex-ante ones, demonstrating regulators' pragmatic attitude to automated trading and market stability in changing technical landscapes.

Seufert et al. [27] mentioned NFV has transformed network structures, improving flexibility, affordability, and scalability. Operators struggle to compare and assess possibilities in this complicated terrain of multifaceted solutions. They used the multi-attribute decision making to combine placement performance metrics into a single score. A comparison review of rankings shows that various methods produce comparable results, suggesting that placements with good scores across multiple methods may be suitable for automated decision-making. This study illuminates the difficulties and possibilities of coordinating NFV-based networks and suggests ways to improve decision-making in complicated network contexts.

Koziel et al. [28] introduce a method for improving electromagnetic driven optimization methods for small microwave components. The method uses intelligent decision-making to alter design specifications to overcome issues with poor initial designs. The technique dynamically adjusts design objectives such target operating frequencies and bandwidths using local iterative search routines, mostly gradient-based descent algorithms. The technique automates and adapts design adjustments during optimization using knowledge-based methodologies and indicators of convergence state, frequencies spread, and incompatibility between actual and intended operating conditions. Design specification alterations are activated and regulated by strict criteria. The approach is tested in three micro-strip circuits: single-band and dual-band branch-line couplers and a dual-band power divider. The results show the suggested methodology's significant reliability improvement, which could improve EM-driven layout optimizations for tiny microwave components.

Jiang et al. [29] provide a computational approach to help robots make risky judgments like humans. They use regret theory to create a quantitative decision-making model for these psychological events. They convert the model into a state-space description and create a fuzzy logic controller to gather preference data from decision-makers to quantify it. After training the model with data from individual participants, a quantitative model explains the psychological underpinnings of risk mindsets in human decision-making. The model's accuracy in forecasting is carefully validated and averages 74.7%, which matches the subjects' decision accuracy. The model has an average precision of 86.6% when considering only repeated subject decisions.

Zhang et al. [30] introduced an optimization-embedded reinforcement learning (OERL) is used to help automated vehicles navigate roundabouts make adaptive decisions. Model-based optimization in the Actor-Critic framework allows continuous behavior exploration in the action space, allowing macro-scale behavior and medium-scale behavior to be determined at the same time with high sample efficiency. The redesigned actor component mimics human drivers' macro-scale cognitive leaps and dynamically adjusts medium-scale behaviors through driving skills. Experimental assessments evaluate the algorithm's effectiveness and learning driving strategy to fixed medium-scale behavior decision-making. OERL can quickly adapt to changing surroundings, including untrained roundabouts and dangerous situations. The method's excellent algorithm efficiency and increased system performance suggest it could improve autonomous vehicle making choices in dynamic roundabouts.

2.2 Research gaps

Chen et al. [31] introduced a deep learning object recognition system for Hsinchu-scenic-spot recognition. The framework is based on the YOLOv3 calculation inside the TensorFlow simulated intelligence System. This Hsinchu-grand spot acknowledgment framework, named HsinchuFun, engages clients to catch pictures of beautiful spots utilizing the camera on an Android Application terminal gadget, distinguishing the beautiful spots in Hsinchu, Taiwan. Through the Hsinchu city government information open platform, the model includes features like dynamic itinerary planning, information on 77 Hsinchu-scenic spots, and Google MAP navigation. The article investigation framework effectively recognizes 28 Hsinchu-grand spots, accomplishing an exactness of the item locator with IoU=0.6 and Guide coming to 88.63%. From the literature review [21]-[31], we have proposed several AI models for tourist scenic spot recognition which faces the several challenges that impact the accuracy and reliability of the recognition process. One significant issue stems from the complexity of environments commonly encountered in tourist destinations, where diverse lighting conditions and surroundings can pose difficulties for AI algorithms [21][22]. Additionally, the variability in image quality, with tourists capturing images of varying resolutions and clarity, presents a hurdle for models to process distorted or low-quality pictures accurately [23]. The restricted accessibility of exhaustive and various preparation information can upset the model's capacity to sum up to new and concealed areas, affecting recognition performance [24][25]. The dynamic nature of tourist spots, influenced by changing seasons, weather conditions, and human activities, adds complexity to maintaining accurate recognition over time [26]. Cultural and regional variances in architectural styles and landmarks may challenge AI models in distinguishing between unique features, especially when biased datasets are used. Interference from tourists and crowded conditions introduces complications, requiring models to adapt to obstructed views and occlusions [27]. Real-time processing challenges, where quick and accurate results are essential for enhancing the tourist experience, demand efficient algorithms capable of handling resource-intensive scenarios [28][29]. Ethical considerations related to privacy and the responsible use of AI in tourist recognition systems adds another layer of complexity that requires careful navigation. Addressing these challenges necessitates ongoing research and advancements in computer vision and machine learning to develop more robust and adaptable AI models for tourist scenic spot recognition [30][31]. To address those problems, we develop the AI driven smart scenic management model to analyze the picture carefully to detect tourist scenic spot. The research objectives of proposed work are given as follows.

1. Develop and implement an advanced algorithm to enhance feature extraction in tourist scenic spot recognition. Evaluate the algorithm's efficacy in selecting optimal features from diverse datasets, ensuring improved accuracy and robustness.
2. Integrate the AI into the existing model to improve the detection accuracy of tourist scenic spots. Investigate the impact of AI on capturing temporal dependencies within image sequences, leading to more accurate recognition outcomes.
3. Assess the user experience and practical applicability of the AI-driven smart scenic management model in real-world scenarios. Engage with potential users, such as tourists in Hsinchu, to gather feedback on the model's usability, effectiveness, and overall satisfaction.
4. Collect a comprehensive dataset of tourist scenic spots, particularly focusing on Hsinchu City, Taiwan. Conduct rigorous performance evaluation of the model, comparing it with existing models based on accuracy, precision, recall, and mean average precision metrics.

3. PROPOSED METHODOLOGY

The system architecture of the proposed AI-driven smart scenic management model, as shown in Fig. 1, encompasses three distinct phases to provide an intelligent and efficient solution for tourist spot recognition in Hsinchu City, Taiwan. In the initial phase, a tourist dataset is created, incorporating details such as Scenic spots, Celebrations and preferential information, Passenger flow and traffic conditions, Weather and travel insights, and details related to Parking and emergency rescue. The dataset serves as the foundation for subsequent phases. The second phase involves tourists interacting with the system by utilizing their mobile phones to search for places. Tourists provide reference images captured in proximity to Hsinchu City, Taiwan. These images, acting as queries, initiate the scenic spot recommendation service provided by the system. The third and crucial phase, known as the scenic spot recommender, encompasses several key steps to ensure accurate and efficient tourist scenic spot detection. The original dataset is augmented to create an enriched dataset that enhances the model's ability to generalize and recognize diverse scenic spots. Input images from the augmented dataset undergo thorough preprocessing to eliminate noise and unwanted artifacts, ensuring the clarity and quality of images for subsequent analysis. The feature extraction and optimization process are executed using the modified golden jackal optimization (MGJO) algorithm, which selectively identifies the most relevant and optimal features among the multiple available features. It significantly contributes to the overall efficiency of the model. The final step involves the use of a deep multi-layer recurrent neural network (DM-RNN) for tourist scenic spot detection.

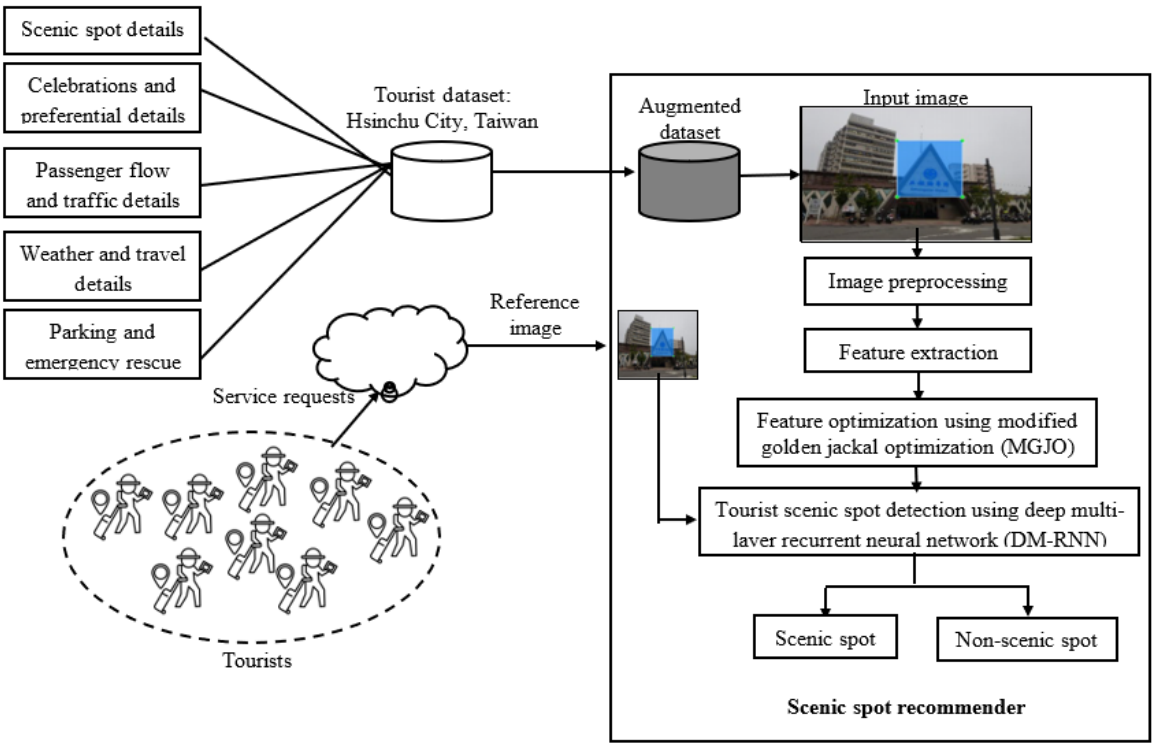

Fig. 1 System architecture of proposed AI-driven smart scenic management model

The framework orders identified objects into beautiful spot and non-picturesque spot classifications. The AI-driven smart scenic management model provides an intelligent, accurate, and efficient solution for locating and exploring scenic locations in Hsinchu City, Taiwan, by seamlessly integrating these three phases. The use of cutting-edge algorithms and deep learning guarantees trustworthy recommendations, enhancing the tourist experience.

4.1 Feature extraction and optimization

Highlight extraction and improvement assume essential part in upgrading the effectiveness of the proposed man-made intelligence driven shrewd grand administration model. In this unique circumstance, the model consolidates the altered modified golden jackal optimization (MGJO) calculation to perform highlight extraction and improvement. This algorithm's primary goal is to carefully evaluate and select the best features from a wide range of possibilities. The process of identifying and isolating relevant information from the input images, as well as capturing distinct patterns or characteristics that are necessary for accurate scenic spot detection, is known as feature extraction. The MGJO calculation refines this extraction interaction by shrewdly exploring through the element space and knowing the highlights that contribute most essentially to the model's general exhibition. It makes use of optimization techniques to fine-tune the features that were chosen, making sure that they are in sync with the particular requirements of recognizing tourist attractions in Hsinchu City, Taiwan. Basically, the utilization of the MGJO calculation in highlight extraction and improvement is equipped towards making a smoothed out and exceptionally powerful arrangement of elements that significantly upgrade the exactness and dependability of the model. It guarantees that the model is furnished with the most relevant data, permitting it to pursue educated and exact choices during the traveler grand spot identification stage. The usage of cutting edge improvement procedures adds to the power of the model, making it appropriate for the changed and dynamic scene of place of interest acknowledgment. To efficiently navigate the feature space and select the most advantageous features from a pool of possibilities, it consists of several intricately designed steps.

- In the instatement stage, a populace of potential arrangements is made, each addressing various arrangements of elements, with irregular or explicit introductions.
- The goal capability is then assessed for every arrangement, estimating its presentation or wellness in light of the issue prerequisites. The solutions are ranked according to how fit they are, and then a selection process is used to pick the ones with the highest rankings and the best fitness.
- One of the particular highlights of the MGJO calculation is the presentation of a brilliant jackal development procedure. This methodology includes changing the component upsides of the chose arrangements, finding some kind of harmony between worldwide investigation and nearby double-dealing.
- Worldwide investigation guarantees wide pursuit across the arrangement space, while nearby double-dealing calibrates arrangements in promising locales. It iteratively refreshes the arrangements in light of the presented developments, refining the component values to accomplish further developed wellness.
- Termination criteria, such as a maximum number of iterations or reaching a satisfactory fitness level, are defined to determine when the algorithm should stop. The final output of the MGJO algorithm is the best solution obtained during the optimization process.

This feature extraction and optimization contributes significantly to enhancing the accuracy and reliability of the subsequent tourist scenic spot detection process. The victim location matrix (T) is generated in the initial step at random.

$$T = \begin{bmatrix} T_{1,1} & \dots & T_{1,h} & \cdots & T_{1,m} \\ T_{2,1} & \cdots & T_{2,h} & \dots & T_{2,m} \\ \dots & \cdots & \cdots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ T_{M-1,1} & \cdots & T_{M-1,h} & \cdots & T_{M-1,m} \\ T_{M,1} & \cdots & T_{M,h} & \cdots & T_{M,m} \end{bmatrix} \tag{1}$$

where M is the number of victims and m is the number of measurements. The Golden Fox Hunt's mathematical model is as follows (|W| > 1):

$$T_1(r) = T_N(r) - W \cdot \left| T_N(r) - ek.\,prey(r) \right| \tag{2}$$

$$T_2(r) = T_{DN}(r) - W \cdot \left| T_{DN}(r) - ek.\,prey(r) \right| \tag{3}$$

where prey (r) is the position vector of the prey, $T_N(r)$ is the position of the male golden fox, $T_{DN}(r)$ is the position of the female, and r is the current iteration.

$$W = W_1 \cdot W_0 \tag{4}$$

$$W_1 = X_1 \cdot \left(1 - (r / R)\right) \tag{5}$$

where "R" is a random number vector and calculated using the Levy flight function, W_0 and W_1 represents the distance between the golden fox and the prey which define as follows.

$$ek = 0.05 = KD(T) \tag{6}$$

$$KD(T) = 0.01 \times (\eta \times \rho) / \left(\left| \kappa^{\left(1/\beta\right)} \right| \right) \rho = \left\{ \frac{\Omega(1+\delta) \times Sin\left(\Delta \delta/2\right)}{\Omega\left(\frac{1+\delta}{2}\right) \cdot \times \delta \times \left(2^{\delta-1}\right)} \right\}^{1/\delta} \tag{7}$$

where T and R are random numbers (0, 1), and is always set to 1.5.

$$T(r+1) = \frac{T_1(r) + T_2(r)}{2} \tag{8}$$

where T(r+1) is the updated hunting position for both male and female golden foxes is T(r + 1). The dodge power decreases as the golden foxes pursue their prey.

$$T_1(r) = T_N(r) - W \cdot \left| T_N(r) - ek.\, prey(r) \right| \tag{9}$$

$$T_2(r) = T_{DN}(r) - W \cdot \left| T_{DN}(r) - ek.\, prey(r) \right| \tag{10}$$

The working process of feature extraction and optimization is summarized in Algorithm 1. By incorporating the MGJO, the model enhances its ability to navigate the complex feature space associated with tourist datasets. This optimization algorithm intelligently selects and refines features, ensuring that the most relevant and discriminative characteristics are extracted. As a result, the feature representation becomes more robust and tailored to the nuances of scenic spots, contributing to a higher level of accuracy in subsequent recognition tasks.

Algorithm 1 Feature extraction and optimization using MGJO

```
Input   : The population size M and maximum number of iterations R
Output : Feature optimization

Initialize the random prey population T; ( i = 1, 2 ,...,M)
While (r <R)
Calculate the fitness values of prey
T1 = best prey individual (male jackal position)
T2 = second best prey individual for each prey individual
Update the evading energy "W"
Update "e!" using the threshold condition
If (|W| < 1) (Exploration phase)
Update the prey position
If (|W| > 1) (Exploitation phase)
Update the prey position
End for
r = r + 1
End while end while
Return T1
```

4.2 Detection of tourist scenic spot

The identification of vacationer picturesque spots inside the proposed simulated intelligence driven savvy grand administration model is enhanced by the utilization of the deep multi-layer recurrent neural network (DM-RNN). When it comes to situations where it is absolutely necessary to recognize intricate patterns and temporal dependencies, this cutting-edge architecture of neural networks is of the utmost importance for enhancing the detection accuracy. The DM-RNN is described by its complex construction and repetitive associations, which empower it to really catch and interaction successive data. With regards to traveler picturesque spot discovery, where the spatial and transient qualities of highlights assume an essential part, the DM-RNN ends up being a significant resource. It succeeds in learning and understanding the logical connections between various components inside the vacationer datasets. By utilizing the abilities of the DM-RNN, the model becomes proficient at taking care of dynamic and advancing scenes related with vacation spots. This remembers varieties for traveler stream and traffic, changes in weather patterns, and the powerful idea of festivities and special data. The repetitive associations in the organization engage it to hold and use past data, upgrading its capacity to pursue informed choices during the location cycle. The layers inside the DM-RNN add to capacity to catch fleeting conditions and figure out complex examples.

1. The information layer is utilized for getting the consecutive information. This could be the preprocessed and optimized features obtained through the modified golden jackal optimization

(MGJO) algorithm in the context of tourist scenic spot detection.

2. Intermittent layers are a urgent part of the DM-RNN, empowering the organization to keep a memory of past states and catch transient conditions. Understanding sequential patterns is made easier thanks to these layers' ability to preserve information over multiple time steps.
3. Secret layer of DM-RNN add to the organization's capacity to learn various leveled portrayals of the info information. The sequential information is processed by these layers, and the features that are relevant to the detection task are extracted.
4. The result layer creates the end-product of the organization's handling. The output layer may make predictions about whether an input corresponds to a scenic spot in the case of tourist scenic spot detection.

The specific design choices made during model development determine the precise architecture of the DM-RNN, including the number of recurrent layers, hidden layers, and neurons in each layer. It is widely used models for sequence data. Similar to feed-forward networks, it has become common to construct DM-RNN, which involves stacking many successive layers to obtain a high-level summary of the data. However, this only works on a few layers. In this section, we discuss the mathematics of RNNs, with special emphasis on gradient back propagation. An RNN cell is a nonlinear transformation that maps the input signal p_s at time t and the hidden state of the previous time step s−1 to the current hidden state i_s :

$$i_s = F(p_s, i_{s-1}, Z) \quad (11)$$

Here Z is the cell's training parameter. Input sequences have a common length S, which can vary. Whether the final state i_S or the entire sequence of states { i_s } or the target prediction requiring a single sequence label, the estimated loss L depends on the task. The study involves adjusting Z to minimize losses via standard uniform gradient descent. When multiple RNN cells are stacked together, the hidden state of the lower L−1 is sent as input to the next higher level.

$$i_s^L = F(i_s^{L-1}, i_{s-1}^L, z) \quad (12)$$

Temporal dilation results in a two-dimensional lattice of depth L and length S. The gradients flow in opposite directions: in each cell the gradient. The loss of the output gate is used to calculate the slope with respect to weight, input and previous latent state. The last two gradients propagate through their gates to the preceding cells in time and depth. Next, we discuss how the magnitude of these gradients varies along the grid. The analysis, supported by numerical simulations, shows that typical RNN cells are biased to minimize or maximize gradients, thereby impeding the training of deep recurrent networks. The slope weight that can be trained in a cell on the optimal solution is compute as follows.

$$j_z = \frac{\partial i_s^L}{\partial z} ji_s^L \quad (13)$$

Here $\frac{\partial i_s^L}{\partial z}$ denotes the Jacobian matrix and ji_s^L is the column vector containing the partial derivatives of loss. The output (hidden) state of the cell is based on the Jacobian gradients act as a "gain matrix" and their magnitudes must be averaged to prevent them from vanishing or exploding. By expanding the slope, we get the frequency for the distribution j_s^L

$$ji_s^L = \frac{\partial i_s^{L+1}}{\partial i_s^L} ji_s^{L+1} + \frac{\partial i_{s+1}^L}{\partial i_s^L} ji_{s+1}^L = G_s^{L+1} ji_s^{L+1} + I_{s+1}^L ji_{s+1}^L \quad (14)$$

Input with G_s^L Jacobian and I_s^L Jacobian hidden status We want the magnitude $\| ji_s^L \|_2$ of the gradient to be constant for arbitrary L and s. It is difficult to fully specify this size because correlations can occur, for example ji_s^{L+1} and ji_{s+1}^L , due to weight distribution. However, it is clear that the G_s^{L+1} and I_{s+1}^L Jacobians play a fundamental role: if their singular values are small, they reduce the gradients and sooner or later disappear. If their singular values are large, they increase the gradients and cause them to explode. 1 Next, we analyze the behaviour of two matrices for two widely used RNN cells. We first consider a very simple RNN cell, henceforth called DM-RNN. We formulate the final hidden layer as follows.

$$i_s^L = \tan i\,(Z_p i_s^{L-1} + Z_i i_{s-1}^L + n) \quad (15)$$

Then we get the two Jacobians as follows.

$$G_s^L = C_{\tan i}(Z_p i_s^{L-1} + Z_i i_{s-1}^L + n)', Z_p \quad (16)$$

$$I_s^L = C_{\tan i}(Z_p i_s^{L-1} + Z_i i_{s-1}^L + n)', Z_i \quad (17)$$

where C_p denotes a diagonal matrix with the p elements of the vector as diagonal entries. To test the assumption and calculates the average gradient magnitude.

$$G_s^L = C_{\tan i(d_s^L)} C_{(o_s^L)}, Z_{po} + C_{\tan i(d_s^L)}, C_{(o_s^L)}(C_{d_{s-1}^L} C_{(F_s^L)}, Z_{pF} + C_{w_s^L} C_{(h_s^L)}, Z_{ph} + C_{h_s^L} C_{(w_s^L)}, Z_{pw}) \quad (18)$$

$$I_s^L = C_{\tan i(d_s^L)} C_{(o_s^L)}, Z_{io} + C_{\tan i(d_s^L)}, C_{o_s^L} (C_{d_{s-1}^L} C_{(F_s^L)}, Z_{iF} + C_{w_s^L} C_{(h_s^L)}, Z_{ph} + C_{i_s^L} C_{(w_s^L)}, Z_{iw}) \tag{19}$$

Random orthogonal matrices were chosen for the latent levels and biases for 0 and weights. Input sequences and correlation factor α = 0.5 are generated. The continuous function of the DM-RNN model is define as follows.

$$h_s^L = \sigma(Z_{ph} i_s^{L-1} + Z_{ih} i_{s-1}^L + n_h) \tag{20}$$

$$F_s^L = \sigma(Z_{pF} i_s^{L-1} + Z_{iF} i_{s-1}^L + n_F) \tag{21}$$

$$o_s^L = \sigma(Z_{po} i_s^{L-1} + Z_{io} i_{s-1}^L + n_o) \tag{22}$$

$$w_s^L = \tan i(Z_{pw} i_s^{L-1} + Z_{iw} i_{s-1}^L + n_w) \tag{23}$$

$$d_s^L = F_s^L \circ d_{s-1}^L + h_s^L \circ w_s^L \tag{24}$$

$$h_s^L = o_s^L \circ \tan i(d_s^L) \tag{25}$$

where h, F, and O are the input, forget, and output gate activations, respectively, and d is the state of the cell. Revelations of Jacob is C_p the p elements of the vector represent a diagonal matrix as diagonal entries. The functions are a bit more complicated, but still suitable for the same type of analysis. We again choose the same example conditions as in the DM-RNN above, namely hidden conditions and biases equal to zero and orthogonal weight matrices. By substituting numerical values into the above equations, we see that the sigmoid function reduces the singular value of the two Jacobians to 0.25. The working process of tourist scenic spot detection using DM-RNN technique is summarized in Algorithm 2.

Algorithm 2 Tourist scenic spot detection using DM-RNN

Input : Number of features, optimal best features, and reference images

Output : Tourist scenic spot detection - scenic spot and non-scenic spot

1. Initialize the random population
2. Define previous time step s−1 of current hidden state $i_s : i_s = F(p_s, i_{s-1}, Z)$
3. If i=0 , j=1
4. While **Do**
5. Compute weight vector for each bar $j_z = \frac{\partial i_s^L}{\partial z} j i_s^L$
6. Find the frequency of each distribution model j_s^L

   $$j i_s^L = \frac{\partial i_s^{L+1}}{\partial i_s^L} j i_s^{L+1} + \frac{\partial i_{s+1}^L}{\partial i_s^L} j i_{s+1}^L = G_s^{L+1} j i_s^{L+1} + I_{s+1}^L j i_{s+1}^L$$

7. Compute recurrence states $i_s^L = \tan i(Z_p i_s^{L-1} + Z_i i_{s-1}^L + n)$
8. Else
9. End if
10. Update the final value
11. End

4. RESULTS AND DISCUSSION

In this section, we present the outcomes and comparative analysis of the proposed deep multi-layer recurrent neural network (DM-RNN) model with existing state-of-the-art tourist scenic spot detection models. The validation of the DM-RNN model is conducted using the Hsinchu-scenic-spot dataset, with additional data augmentation techniques employed to enhance detection accuracy. The entire workflow of the proposed approach is implemented using the Python programming language with various libraries. The results obtained from the DM-RNN model are compared against established models, including the faster region convolutional neural network (FR-CNN), single-shot multi box detector (SSD), and you only look once version 3 (YOLOv3) [31]. Performance evaluation is conducted using diverse metrics such as accuracy, precision, recall, and F-measure for assessment of the proposed model's effectiveness in tourist scenic spot detection.

4.1 Dataset description

Tourists can establish a connection between the XAMPP server and the MySQL database, referred to as the database server, via an Android-based application. Subsequently, XAMPP conducts user identity authentication. Once the system verifies the user's identity, they gain the ability to explore scenic spots, access introductions to popular locales, plan itineraries, and navigate through images of scenic spots. When a user queries a scenic spot using a picture, the application uploads the photo to the database. XAMPP transfers the image to the YOLOv3 object analysis system, based on the Tensorflow AI framework, for analysis and identification of the scenic spot in the picture. After the analysis concludes, the results are sent back to the XAMPP server, stored in the database, and then relayed to the application user. Originally, the system utilized the Intel® Core™ i9-9900KF CPU @ 3.60 GHz as the training computing core for the object analysis system. However, due to inefficiencies leading to a 3-day training duration for 100 iterations, the system incorporated GPU-assisted computing with the GeForce® GTX 2060. The parallel computing architecture CUDA and GPU acceleration library DNN were employed to enhance the speed and efficiency of thematic training. This adjustment remarkably reduced the training time from 3 days to 30 minutes, accelerating the training speed by 144 times. Supported by the OpenCV computer vision library, the system provides rapid image processing, computer vision, and image recognition. The research team contributed to the image dataset by personally visiting 28 scenic spots in the Hsinchu area and capturing a total of 15,351 images. This enriched the system's capabilities in providing detailed introductions and descriptions of scenic spots. Beyond the identification of these 28 spots, the system dynamically retrieves the list of tourist attractions in Hsinchu City from the Hsinchu City Government Information Open Platform, incorporating information on 77 scenic spots in Hsinchu. For data augmentation, various processes such as rotation, zooming in and out, adding Gaussian noise, salt noise, pepper noise, and grayscale transformation were employed. After data augmentation, the system utilized the augmented dataset to enhance the training and testing phases. The augmented dataset included 1,228,000 images for training and 307,100 images for testing. The total dataset, combining both the original and augmented images, amounted to 1,535,100 images.

Table 1 Dataset description

S. No	Scenic spots	Original dataset		Augmented dataset	
		Training	Testing	Training	Testing
1	Auditorium	435	110	43500	11000
2	Big city	435	110	43500	11000
3	Black bat	435	110	43500	11000
4	Central park	435	110	43500	11000
5	Chiaotung university	435	110	43500	11000
6	Chungchengtail night market	450	110	45000	11000
7	Chunghua university	445	110	44500	11000
8	City god temple	435	110	43500	11000
9	Culture office	435	110	43500	11000
10	Far eastern	450	110	45000	11000
11	Fire museum	435	110	43500	11000
12	Hsinchu city hall	450	110	45000	11000
13	Hsinchu Confucius temple	435	110	43500	11000
14	Hsinchu museum	435	110	43500	11000
15	Hsinchu stadium	435	110	43500	11000
16	Hsinchu zoo back	435	110	43500	11000
17	Hsinchu zoo front	450	110	45000	11000
18	Hsuanchuuang university	435	110	43500	11000
19	Image museum	435	110	43500	11000
20	J.piin city	435	110	43500	11000
21	Lichih park	450	106	45000	10600
22	m_building	435	110	43500	11000

23	Railway museum	435	110	43500	11000
24	Sanhsiangchiao train station	450	110	45000	11000
25	Hsinchu train station	435	105	43500	10500
26	Tsinghua university	435	110	43500	11000
27	Village museum	435	110	43500	11000
28	Yuanpei university	435	110	43500	11000
Number of images		**12280**	**3071**	**1228000**	**307100**
Total images		**15351**		**1535100**	

Table 1 provides a comprehensive description of the dataset used for training and testing the tourist scenic spot detection models. The dataset is ordered in view of different picturesque spots in Hsinchu City, Taiwan, and incorporates both the first and expanded datasets. In the original and augmented datasets, each scenic spot is listed with the number of images that correspond to it for training and testing purposes. The dataset contains unique images from a variety of locations, including auditoriums, major cities, cultural offices, and universities. For both the original and augmented datasets, the total number of images is calculated, allowing for clear understanding of the scale and diversity of the dataset used for training and evaluating the models.

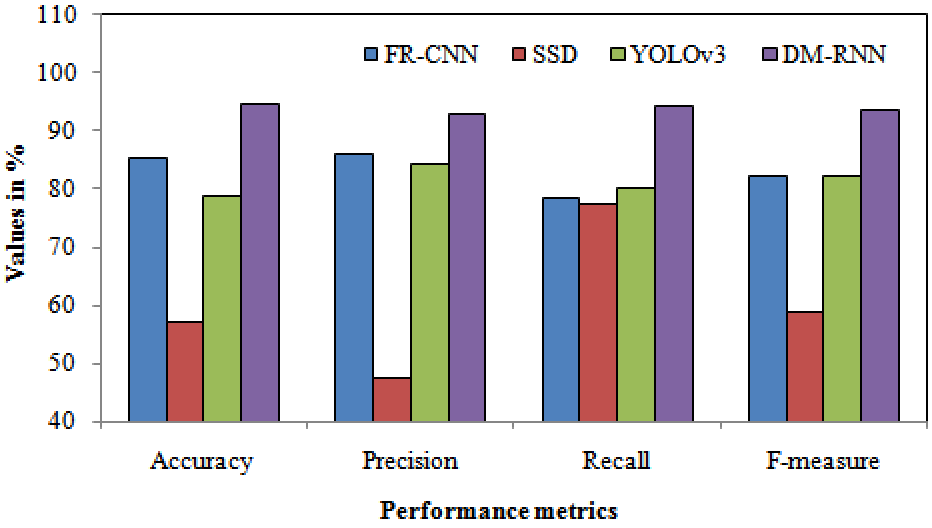

Fig. 2 Results comparison of tourist scenic spot detection models with IoU of 0.5 and original dataset

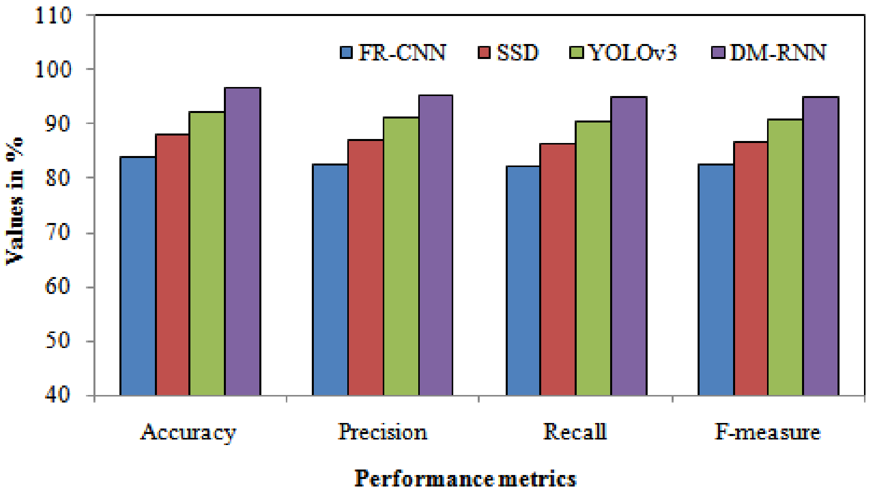

Fig. 3 Results comparison of tourist scenic spot detection models with IoU of 0.5 and augmented dataset

4.2 Results analysis

Table 2 provides a comprehensive comparison of the proposed DM-RNN model to the FR-CNN, SSD, and YOLOv3 tourist scenic spot detection models. The assessment is led with a crossing intersection over union (IoU) limit of 0.5, mirroring the exactness, accuracy, review, and F-measure measurements. Starting with accuracy, DM-RNN emerges as the frontrunner with an impressive 94.568%, shows a substantial improvement compared to FR-CNN (85.136%), SSD (56.896%), and YOLOv3 (78.856%). It emphasizes DM-RNN's capacity to achieve a higher overall correctness in identifying tourist scenic spots. Moving to precision, DM-RNN maintains high precision rate of 93.025%, shows a substantial improvement compared to FR-CNN (86.125%), SSD (47.355%), and YOLOv3 (84.123%). The model's proficiency in minimizing false positives highlights its precision in correctly identifying tourist scenic spots while avoiding unnecessary detections. In terms of recall, DM-RNN achieves 94.247%, exhibiting an improvement over FR-CNN (78.315%), SSD (77.245%), and YOLOv3 (80.124%). This underlines DM-RNN's effectiveness in capturing a higher proportion of actual positive instances, reducing instances of overlooking tourist scenic spots. F-measure, a comprehensive metric balancing precision and recall, shows DM-RNN's dominance with a score of 93.632%, highlighting its superiority over FR-CNN (82.035%), SSD (58.715%), and YOLOv3 (82.075%). The improvement in F-measure underscores DM-RNN's ability to provide a harmonious blend of precision and recall, ensuring a robust overall performance. From Fig. 2, DM-RNN outshines existing models, presenting a substantial improvement in accuracy, precision, recall, and F-measure on the original dataset. Fig. 3 shows the results comparison of tourist scenic spot detection models with an IoU of 0.5 on the augmented dataset provides valuable insights into the models' performance. Starting with accuracy, DM-RNN once again stands out, achieving an impressive 96.534%, demonstrating an improvement compared to FR-CNN (83.829%), SSD (88.064%), and YOLOv3 (92.299%). It shows DM-RNN's robustness in accurately identifying tourist scenic spots, particularly on an augmented dataset. Examining precision, DM-RNN maintains a high precision rate of 95.325%, shows a notable improvement compared to FR-CNN (82.620%), SSD (86.855%), and YOLOv3 (91.090%). The model's precision in minimizing false positives remains a distinctive feature, reinforcing its reliability in providing accurate detections. In terms of recall, DM-RNN achieves 94.865%, demonstrating a significant improvement over FR-CNN (82.160%), SSD (86.395%), and YOLOv3 (90.630%). This underscores DM-RNN's effectiveness in capturing a higher proportion of actual positive instances, even on the augmented dataset. F-measure, a comprehensive metric balancing precision and recall, once again highlights DM-RNN's dominance with a score of 95.094%. This signifies a substantial improvement compared to FR-CNN (82.389%), SSD (86.624%), and YOLOv3 (90.859%). DM-RNN consistently provides a harmonious blend of precision and recall, ensuring a robust overall performance on the augmented dataset.

Table 2 Comparative analysis of proposed and existing tourist scenic spot detection models with IoU of 0.5

Tourist scenic spot detection models	Accuracy	Precision	Recall	F-measure
	Original dataset			
FR-CNN	85.136	86.125	78.315	82.035
SSD	56.896	47.355	77.245	58.715
YOLOv3	78.856	84.123	80.124	82.075
DM-RNN	94.568	93.025	94.247	93.632
	Augmented dataset			
FR-CNN	83.829	82.620	82.160	82.389
SSD	88.064	86.855	86.395	86.624
YOLOv3	92.299	91.090	90.630	90.859
DM-RNN	96.534	95.325	94.865	95.094

Table 3 provides a comparative analysis of proposed and existing tourist scenic spot detection models with an IoU of 0.6. In Fig. 4, the results comparison of tourist scenic spot detection models with an IoU of 0.6 and the original dataset is presented. DM-RNN exhibits remarkable accuracy, reaching 95.012%, showcasing a substantial improvement over YOLOv3 (78.856%), FR-CNN (85.136%), and SSD (56.896%). This emphasizes DM-RNN's superior capability in accurately identifying tourist scenic spots within the original dataset. DM-RNN achieves the highest precision at 94.123%, outperforming YOLOv3 (88.633%), FR-CNN (85.235%), and SSD (43.191%). The precision metric indicates DM-RNN's effectiveness in minimizing false positives, crucial for reliable tourist scenic spot detection. Once again, DM-RNN excels in recall, achieving 94.105%. YOLOv3 follows with 80.124%, FR-CNN with 78.315%, and SSD with 77.245%. The high recall of DM-RNN underscores its proficiency in capturing a substantial portion of actual positive instances. DM-RNN demonstrates the highest F-measure at 94.114%, indicating a well-balanced performance in terms of precision and recall. YOLOv3, FR-CNN, and SSD follow with F-measure scores of 84.164%, 81.629%, and 55.404%, respectively.

Table 3 Comparative analysis of proposed and existing tourist scenic spot detection models with IoU of 0.6

Tourist scenic spot detection models	Accuracy	Precision	Recall	F-measure
	Original dataset			
FR-CNN	85.136	85.235	78.315	81.629
SSD	56.896	43.191	77.245	55.404
YOLOv3	78.856	88.633	80.124	84.164
DM-RNN	95.012	94.123	94.105	94.114
	Augmented dataset			
FR-CNN	80.882	79.905	79.129	79.515
SSD	86.251	85.274	84.498	84.884
YOLOv3	91.620	90.643	89.867	90.253
DM-RNN	96.989	96.012	95.236	95.622

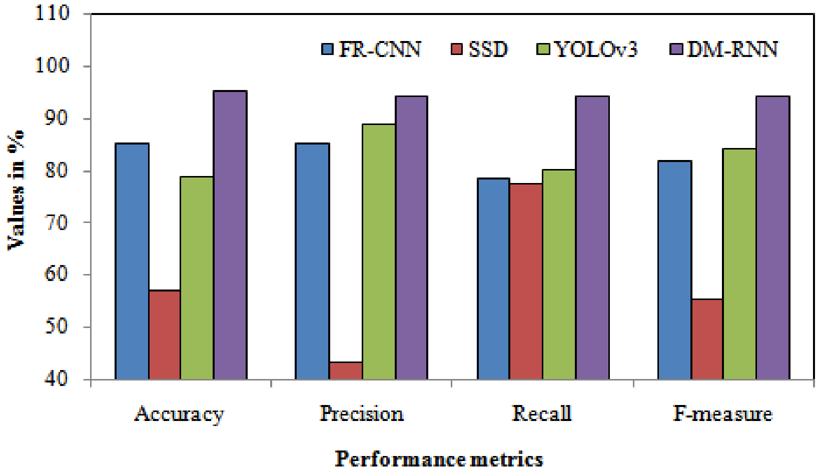

Fig. 4 Results comparison of tourist scenic spot detection models with IoU of 0.6 and original dataset

In Fig. 5, the results comparison of tourist scenic spot detection models with an IoU of 0.6 is presented, this time using the augmented dataset. DM-RNN exhibits exceptional accuracy at 96.989%, shows a substantial improvement over YOLOv3 (91.620%), FR-CNN (80.882%), and SSD (86.251%). This indicates DM-RNN's superior capability in accurately identifying tourist scenic spots within the augmented dataset, demonstrating robustness to variations introduced during augmentation. DM-RNN achieves the highest precision at 96.012%, surpassing YOLOv3 (90.643%), FR-CNN (79.905%), and SSD (85.274%). The precision metric highlights DM-RNN's effectiveness in minimizing false positives, crucial for reliable tourist scenic spot detection, even with augmented data. DM-RNN excels in recall, achieving 95.236%, indicating its proficiency in capturing substantial portion of actual positive instances within the augmented dataset. YOLOv3 follows with 89.867%, FR-CNN with 79.129%, and SSD with 84.498%. DM-RNN demonstrates the highest F-measure at 95.622%, reflecting a well-balanced performance in terms of precision and recall with the augmented dataset. YOLOv3, FR-CNN, and SSD follow with F-measure scores of 90.253%, 79.515%, and 84.884%, respectively.

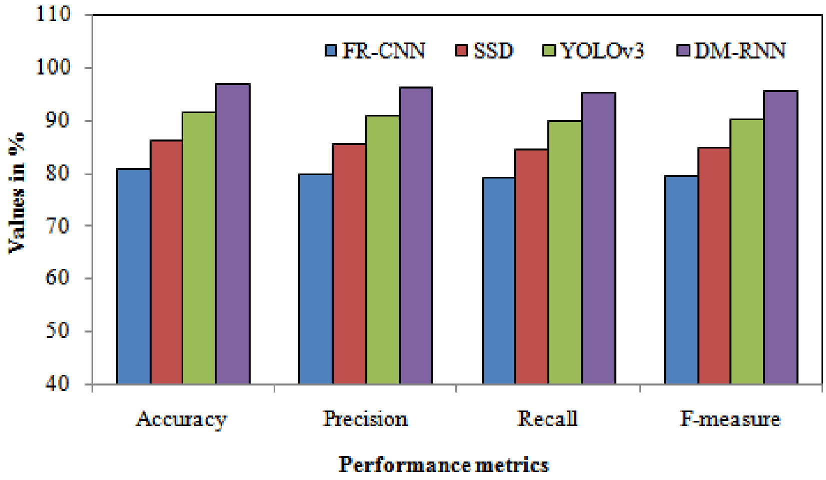

Fig. 5 Results comparison of tourist scenic spot detection models with IoU of 0.6 and augmented dataset

Table 4 provides a comparative analysis of proposed and existing tourist scenic spot detection models with an IoU of 0.7. In Fig. 6, the results comparison of tourist scenic spot detection models with an IoU of 0.7 is presented, utilizing the original dataset. DM-RNN stands out with an impressive accuracy of 95.536%, shows a substantial improvement over YOLOv3 (77.235%), FR-CNN (85.421%), and SSD (57.125%). It indicates DM-RNN's superior capability in accurately identifying tourist scenic spots within the original dataset, demonstrating robustness to variations and complexities inherent in the data. DM-RNN achieves the highest precision at 94.985%, surpassing YOLOv3 (81.505%), FR-CNN (86.013%), and SSD (48.652%). The precision metric highlights DM-RNN's effectiveness in minimizing false positives, crucial for reliable tourist scenic spot detection. DM-RNN excels in recall, achieving 94.235%, indicating its proficiency in capturing a substantial portion of actual positive instances within the original dataset. YOLOv3 follows with 81.563%, FR-CNN with 75.123%, and SSD with 77.568%. DM-RNN shows the highest F-measure at 94.609%, reflecting a well-balanced performance in terms of precision and recall with the original dataset. YOLOv3, FR-CNN, and SSD follow with F-measure scores of 81.534%, 80.200%, and 59.798%, respectively.

Table 4 Comparative analysis of proposed and existing tourist scenic spot detection models with IoU of 0.7

Tourist scenic spot detection models	Accuracy	Precision	Recall	F-measure
	Original dataset			
FR-CNN	85.421	86.013	75.123	80.200
SSD	57.125	48.652	77.568	59.798
YOLOv3	77.235	81.505	81.563	81.534
DM-RNN	95.536	94.985	94.235	94.609
	Augmented dataset			
FR-CNN	80.905	80.435	79.905	80.169
SSD	86.274	85.804	85.274	85.538
YOLOv3	91.643	91.173	90.643	90.907
DM-RNN	97.012	96.542	96.012	96.276

In Fig. 7, the results comparison of tourist scenic spot detection models with an IoU of 0.7 is depicted, utilizing the augmented dataset. DM-RNN achieves outstanding accuracy of 97.012%, showcasing a significant improvement over YOLOv3 (91.643%), FR-CNN (80.905%), and SSD (86.274%). This indicates that DM-RNN excels in accurately detecting tourist scenic spots within augmented dataset, demonstrating robustness and adaptability to diverse image variations. DM-RNN attains the highest precision at 96.542%, surpassing YOLOv3 (91.173%), FR-CNN (80.435%), and SSD (85.84%). The precision metric emphasizes DM-RNN proficiency in minimizing false positives, contributing to more reliable tourist scenic spot detection. DM-RNN outperforms other models in recall with a score of 96.012%, indicating its effectiveness in capturing a substantial portion of actual positive instances within the augmented dataset. YOLOv3 follows closely with 90.643%, FR-CNN with 79.905%, and SSD with 85.274%. DM-RNN exhibits the most noteworthy F-measure at 96.276%, mirroring a reasonable presentation as far as accuracy and review with the expanded dataset. YOLOv3, FR-CNN, and SSD follow with F-measure scores of 90.907%, 80.169%, and 85.538%, respectively.

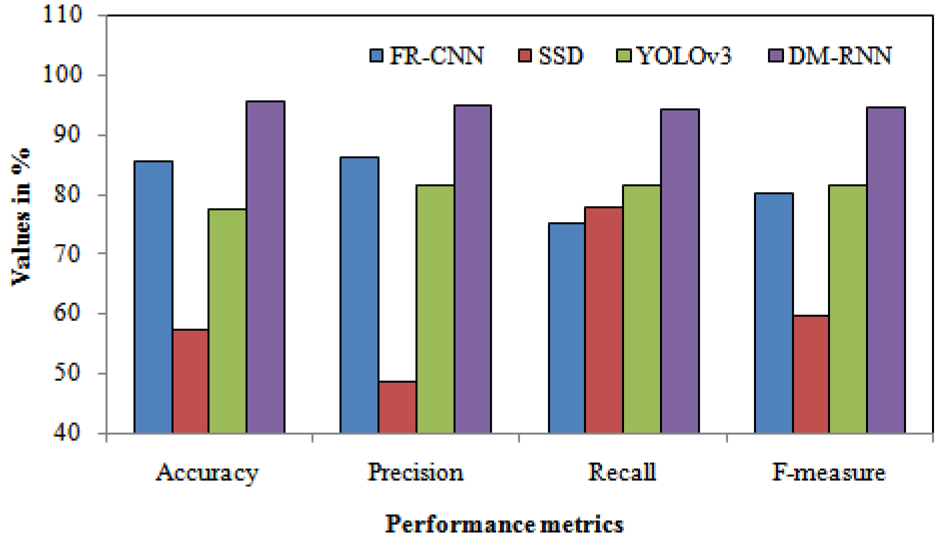

Fig. 6 Comparison of the results between the original dataset and tourist scenic spot detection models with an IoU of 0.7

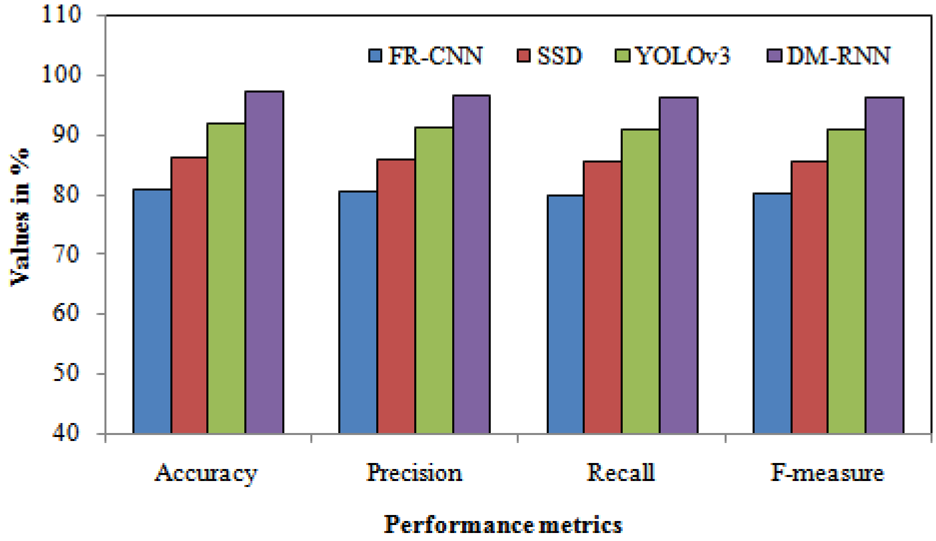

Fig. 7 Results correlation of traveler beautiful spot identification models with IoU of 0.7 and increased dataset.

5. CONCLUSION

Our review presents a creative man-made reasoning driven savvy picturesque administration model intended to add to the financial development of the travel industry. The model consolidates progressed strategies, like the modified golden jackal optimization (MGJO) calculation for productive element extraction and streamlining, choosing the most ideal highlights to upgrade generally speaking execution. The deep multi-layer recurrent neural network (DM-RNN) is utilized for the exact identification of traveler picturesque spots, further raising the accuracy of the acknowledgment interaction. We used a representative case study of tourist attractions in Hsinchu City, Taiwan, as a dataset to assess the efficacy of the proposed model. The executed vacationer picturesque spot acknowledgment model effectively distinguishes and orders 28 conspicuous places of interest in Hsinchu, showing its functional materialness. Breaking down the outcomes, our DM-RNN model shows honorable execution measurements, with a mean typical precision of 95.039% and 96.845% for the first and expanded datasets, individually. In a similar vein, the original dataset's mean average precision is reported to be 94.044 percent, while the augmented dataset's precision significantly rises to 94.96%. These results attest the ability of our model to perceive and arrange vacationer beautiful spots, shown its vigor and versatility precisely. The raised exactness and accuracy measurements, especially in the expanded dataset, highlight the model's adequacy in taking care of different situations and varieties.

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