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Evolution and Stylistic Characteristics of Ancient Chinese Stone Carving Decoration LSTM-DL Approach with Image Visualization

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Abstract: In recent years, advancements in data analysis techniques and deep learning algorithms have revolutionized the field of art and cultural studies. Ancient Chinese stone carving decoration holds significant historical and cultural value, reflecting the artistic and stylistic evolution of different periods. This paper explored the Weighted Long Short-Term Memory Deep Learning (WLSTM – DL) evolution and stylistic characteristics of ancient Chinese stone carving decoration through the application of image visualization techniques combined with a Long Short-Term Memory (LSTM) time-series deep learning architecture. The WLSTM-DL model uses the optimized feature selection with the grasshopper optimization for the feature extraction and selection. By analyzing a comprehensive dataset of stone carving images from different periods, the WLSTM-DL model captures the temporal relationships and patterns in the evolution of stone carving decoration. The model utilizes LSTM, a specialized deep-learning architecture for time-series data, to uncover stylistic characteristics and identify significant changes over time. The findings of this study provide valuable insights into the evolution and stylistic development of ancient Chinese stone carving decoration. The application of image visualization techniques and the WLSTM-DL model showcase the potential of data analysis and deep learning in uncovering hidden narratives and understanding the intricate details of ancient artworks.

Keywords: Image visualization, Stylistic evolution, Grasshopper optimization, Feature extraction and selection.

I. Introduction

Ancient Chinese stone carving decoration is an important cultural heritage that offers insights into the artistic and stylistic evolution of different periods. Analyzing and understanding the patterns and characteristics of these carvings can provide valuable information about the historical and cultural context in which they were created [1]. With the advancements in data analysis techniques and deep learning algorithms, it is now possible to explore these artistic evolutions in a more comprehensive and automated manner [2]. Ancient Chinese stone carving decoration holds a significant place in the cultural heritage of China, offering profound insights into the artistic and stylistic evolution across different periods. These stone carvings are not merely decorative artifacts but bear rich historical and cultural significance, providing a glimpse into the artistic expression, craftsmanship, and cultural context of the times they were created [3]. Analyzing and understanding the intricate patterns and unique characteristics of these carvings can unravel hidden narratives and shed light on the historical, social, and religious aspects prevalent during different periods in ancient China. The exploration of these artistic evolutions has traditionally relied on manual examination and expert knowledge [4]. However, with recent advancements in data analysis techniques and deep learning algorithms, there is now an opportunity to delve into these artistic transformations in a more comprehensive and automated manner [5].

Data analysis techniques and deep learning algorithms have revolutionized various fields, and art and cultural studies are no exception [6]. With leveraging these advancements, researchers can now apply computational methods to analyze vast collections of stone carving images, extracting meaningful insights and uncovering the evolution of stylistic characteristics over time [7]. The combination of data analysis techniques and deep learning algorithms enables researchers to capture the temporal relationships and patterns present in the dataset. These methods can identify significant changes in artistic styles, trace the influences and innovations that shaped the stone carving decoration, and provide a deeper understanding of the cultural and historical context in which these artworks were created [8]. Automated analysis through data-driven approaches allows for a more comprehensive exploration of the vast corpus of ancient Chinese stone carving decoration [9]. Through employing computational models, researchers can uncover hidden connections, identify subtle variations in style, and gain a more nuanced understanding of the development and evolution of these artworks. This not only enhances our knowledge of ancient Chinese culture but also provides a valuable resource for preserving and safeguarding this cultural heritage [10].

In this research paper, the propose a novel approach, the Weighted Long Short-Term Memory Deep Learning (WLSTM-DL) model, to explore the evolution and stylistic characteristics of ancient Chinese stone carving decoration. By combining image visualization techniques with a Long Short-Term Memory (LSTM) time-series deep learning architecture, to capture the temporal patterns and stylistic changes present in the dataset. The application of image visualization techniques and the WLSTM-DL model showcases the potential of data analysis and deep learning in uncovering hidden narratives and understanding the intricate details of ancient artworks. With delving into the artistic and stylistic evolution of ancient Chinese stone carving decoration using advanced computational methods, enrich our understanding of this cultural heritage and gain insights into the dynamic interplay between art, history, and culture. The results of this research have the potential to contribute to the preservation, interpretation, and appreciation of ancient Chinese stone carving decoration, while also inspiring further exploration and research in the field of art and cultural studies.

II. Related works

In this section presented the existing literature associated with the Chainese Stone Carving with the data analytics model. In [11] provides a comprehensive overview of the evolution of stone carving art in ancient China. It explores the stylistic changes and cultural influences that shaped the development of stone carving decoration across different dynasties. The research highlights the significance of stone carving as a cultural heritage and discusses the themes, motifs, and techniques employed in ancient Chinese stone carvings. In [12] focuses on the classification of ancient Chinese stone carving decoration styles. The study proposes a classification framework based on visual features and uses machine learning techniques to automatically categorize and identify the stylistic characteristics of stone carvings. The paper discusses the importance of stylistic classification in understanding the evolution of stone carving art and its cultural significance. In [13] applies deep learning techniques to analyze the artistic characteristics of ancient Chinese stone carvings. The researchers utilize convolutional neural networks (CNNs) to extract visual features and identify stylistic elements present in the carvings. The paper discusses the potential of deep learning in automating the analysis of stone carving art and highlights its contribution to the understanding of cultural heritage. In [14] explores the temporal evolution of ancient Chinese stone carving decoration using data mining techniques. The study analyzes a large dataset of stone carving images from different periods and applies clustering and association rule mining algorithms to identify temporal patterns and stylistic changes. The paper emphasizes the importance of data-driven approaches in uncovering the evolution of artistic styles in cultural artifacts.

In [15] presents a computational analysis of the stylistic evolution of ancient Chinese stone carving decoration. The study proposes a framework that combines image processing techniques, feature extraction, and machine learning algorithms to analyze the visual characteristics of stone carvings. The paper discusses the findings related to the evolution of stylistic features and their implications for understanding the cultural context of ancient China. In [16] conducts a comprehensive study on the stylistic features of ancient Chinese stone carvings. It examines various aspects such as motifs, compositions, and carving techniques to identify the distinct characteristics of different periods. The research contributes to the understanding of the cultural and historical significance of these carvings. In [17] focuses on the analysis of symbolic elements in ancient Chinese stone carving decoration. It explores the symbolic meanings associated with specific motifs and symbols used in the carvings. The research highlights the cultural and religious significance of these symbols and their role in conveying messages and narratives.

In [18] presents a comparative study of the sculptural styles in ancient Chinese stone carving decoration. It examines the characteristics of different styles and identifies the influences and regional variations in the carvings. The research provides insights into the diverse sculptural traditions and their evolution over time. In [19] employs fractal geometry to quantitatively analyze the styles of ancient Chinese stone carving decoration. It measures the fractal dimension of the carvings and explores the relationship between fractal features and artistic styles. The findings contribute to the understanding of the aesthetic principles underlying these artworks. In [20] applies natural language processing techniques to perform semantic analysis of ancient Chinese stone carving decoration. It explores the textual descriptions, inscriptions, and historical records associated with the carvings to gain insights into their cultural and symbolic meanings. The research demonstrates the interdisciplinary nature of studying cultural artifacts. In [21] focuses on the computational analysis of hierarchical structures in ancient Chinese stone carving decoration. It utilizes graph-based algorithms to analyze the relationships and hierarchies present within the carvings. The study provides a deeper understanding of the organizational principles and symbolic representations employed in these artworks. Also, in [22] applies evolutionary algorithms for the stylistic clustering of ancient Chinese stone carving decoration. It uses genetic algorithms and other evolutionary techniques to group similar carvings based on their stylistic features. The research contributes to the automated categorization and classification of these artworks.

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In [23] focuses on the interactive visualization of ancient Chinese stone carving decoration styles. It presents a user-friendly interface that allows researchers and enthusiasts to explore and interact with visual representations of the stylistic characteristics. The research enhances the accessibility and engagement with these cultural artifacts. In [24] employs social network analysis to analyze the cultural influences on ancient Chinese stone carving decoration. It explores the connections, collaborations, and exchanges between artists and workshops to understand the diffusion of stylistic elements. The study provides insights into the cultural dynamics and interactions that shaped these artworks. In [25] focuses on the automated dating of ancient Chinese stone carving decoration using machine learning techniques. It utilizes supervised learning algorithms to predict the approximate time periods of the carvings based on their stylistic features. The research contributes to the development of automated tools for art historical analysis.

III. Methodology

The WLSTM-DL model utilizes a two-step process: feature extraction and selection, and LSTM-based analysis. In the feature extraction and selection step, employ grasshopper optimization, a metaheuristic optimization algorithm, to identify the most relevant and discriminative features from the stone carving images. This optimized feature selection helps reduce the dimensionality of the dataset and improves the model's efficiency and accuracy. Once the features are selected, employ the LSTM architecture, a specialized deep learning model for time-series data analysis. LSTM is designed to capture long-term dependencies and temporal patterns in sequential data, making it suitable for analyzing the evolution of stone carving decoration over time. The WLSTM-DL model leverages LSTM to identify significant changes in stylistic characteristics and extract meaningful insights from the dataset.

To visualize the results and facilitate interpretation, employ image visualization techniques. These techniques allow us to generate visual representations that highlight the patterns, trends, and transitions in the stone carving decoration. By combining the power of deep learning with image visualization, can uncover hidden narratives and gain a deeper understanding of the intricate details of these ancient artworks. A comprehensive dataset of stone carving images from different periods is collected. This dataset serves as the basis for analysis and model training. The collected stone carving images undergo preprocessing steps to enhance their quality and prepare them for analysis. Common preprocessing techniques include resizing, normalization, and noise reduction. Features are extracted from the preprocessed images to represent their visual characteristics. These features capture relevant information such as texture, shape, and color. Various methods can be employed for feature extraction, such as convolutional neural networks (CNNs) or handcrafted feature descriptors.

In order to improve the efficiency and effectiveness of the analysis, feature selection techniques are applied to choose the most informative and discriminative features. Mathematical equations such as correlation coefficients or information gain measures can be used for feature selection.

1.1 Weighted Long Short-Term Memory (WLSTM) Architecture

The WLSTM-DL model, based on the Long Short-Term Memory (LSTM) deep learning architecture, is utilized for capturing the temporal relationships and patterns in the evolution of stone carving decoration. The LSTM model uses a series of equations to process sequential data and model the dependencies over time. The equations governing the LSTM cell include:

Forget Gate: $ft = \sigma(Wf \cdot [ht-1, xt] + bf)$ (1)

Input Gate: $it = \sigma(Wi \cdot [ht-1, xt] + bi)$ (2)

Output Gate: $ot = \sigma(Wo \cdot [ht-1, xt] + bo)$ (3)

Cell State: $\tilde{c}t = tanh(Wc \cdot [ht-1, xt] + bc)$ (4)

Hidden State: $ht = ot \odot tanh(\tilde{c}t)$ (5)

Here equation (1) – (5), ft, it, ot represent the forget gate, input gate, and output gate activations, respectively. $[ht-1, xt]$ denotes the concatenation of the previous hidden state ht-1 and the current input xt. σ denotes the sigmoid activation function, tanh denotes the hyperbolic tangent activation function, $\odot$ denotes element-wise multiplication, and $Wf, Wi, Wo, Wc, bf, bi, bo, bc$ represent the weight matrices and bias terms of the LSTM model. The figure 1 illustrated the flow process of the LSTM model with the proposed WLSTM-DL.

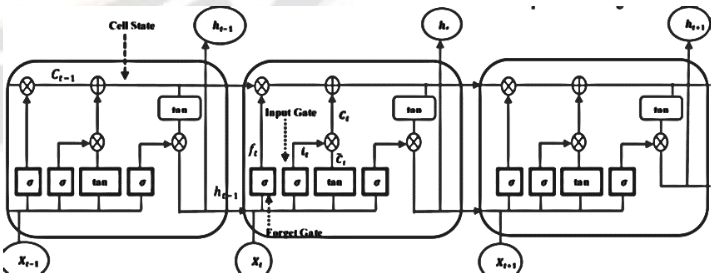

Figure 1: Flow of LSTM Process

Grasshopper Optimization Algorithm (GOA) is employed for feature extraction and selection within the WLSTM-DL model. GOA is a metaheuristic optimization algorithm inspired by the foraging behavior of grasshoppers. It uses mathematical equations to model the movement and search behavior of grasshoppers within a search space. In LSTM cell

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consists of several components: input gate, forget gate, output gate, and cell state. Each component is governed by its own set of equations. The forget gate determines which information from the previous hidden state and the current input should be discarded. It is computed using the sigmoid activation function. The forget gate equation is presented in (6)

$$ft = \sigma(Wf \cdot [ht{-}1, xt] + bf) \qquad (6)$$

In equation (6) ft represents the forget gate activation, Wf is the weight matrix for the forget gate, $ht - 1$ is the previous hidden state, xt is the current input, and bf is the bias term for the forget gate. The input gate controls the information that will be stored in the cell state. It is computed using the sigmoid activation function. The input gate equation is stated in equation (7):

$$it = \sigma(Wi \cdot [ht{-}1, xt] + bi) \qquad (7)$$

Here, it represents the input gate activation, Wi is the weight matrix for the input gate, ht-1 is the previous hidden state, xt is the current input, and bi is the bias term for the input gate. The update cell state equation calculates the new candidate values to be added to the cell state. It uses the hyperbolic tangent (tanh) activation function. The update cell state equation is given in equation (8)

$$\tilde{c}t = tanh(Wc \cdot [ht{-}1, xt] + bc) \qquad (8)$$

Here, c̃t represents the candidate cell state, Wc is the weight matrix for the update cell state, ht-1 is the previous hidden state, xt is the current input, and bc is the bias term for the update cell state. The update cell state equation combines the previous cell state and the new candidate values to update the cell state. The update cell state equation is presented in equation (9)

$$ct = ft \odot ct{-}1 + it \odot \tilde{c}t \qquad (9)$$

Here, ct represents the updated cell state, ft is the forget gate activation, ct-1 is the previous cell state, it is the input gate activation, and c̃t is the candidate cell state. The output gate controls the information that will be output from the LSTM cell. It is computed using the sigmoid activation function. The output gate equation is given in equation (10)

$$ot = \sigma(Wo \cdot [ht{-}1, xt] + bo) \qquad (10)$$

Here, ot represents the output gate activation, Wo is the weight matrix for the output gate, ht-1 is the previous hidden state, xt is the current input, and bo is the bias term for the output gate. The hidden state is computed by applying the output gate activation to the updated cell state using the hyperbolic tangent (tanh) activation function stated in equation (11)

$$ht = ot \odot tanh(ct) \qquad (11)$$

In equation (11), ht represents the hidden state, ot is the output gate activation, ct is the updated cell state. LSTM uses these equations to regulate the flow of information through time and learn long-term dependencies in sequential data. The forget gate determines what information to forget, the input gate determines what information to store, the update cell state combines the previous cell state with new candidate values, and the output gate controls the output information. The hidden state represents the output of the LSTM cell, capturing the relevant information learned from the sequence. Figure 2 illustrated the flow chart of the proposed WLSTM-DL model.

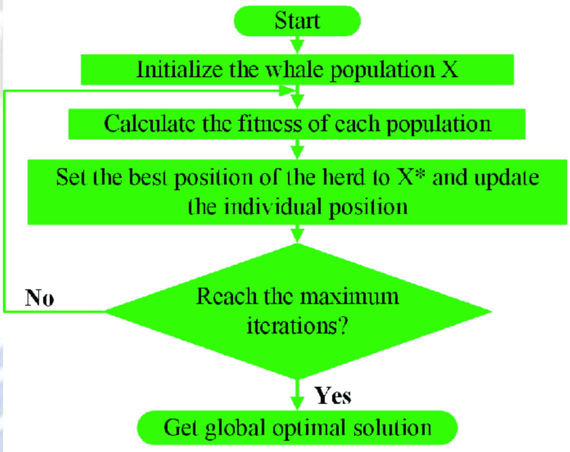

Figure 2: Flow Chart of GOA

In the WLSTM-DL approach for the evolution and stylistic characteristics of ancient Chinese stone carving decoration, Grasshopper Optimization Algorithm (GOA) is utilized for feature extraction and selection. GOA is a metaheuristic optimization algorithm inspired by the foraging behavior of grasshoppers. It is employed to select the most informative and relevant features from the dataset for further analysis. Here is the mathematical representation of feature selection with Grasshopper Optimization: Initially, each feature is assigned a random value within its predefined range. The feature vector as $F = [f1, f2, ..., fn]$, where n is the total number of features. An objective function is defined to evaluate the quality of the feature subset. The objective function measures the fitness or suitability of a feature subset based on the desired criteria. It can be customized based on the specific goals of the study. Let's denote the objective function as OBJ(F), which takes the feature vector F as input and returns a scalar value representing the fitness of the feature subset. The movement of each grasshopper in the optimization process is governed by movement equations. These equations determine the position update of the grasshoppers based on their current positions and the influence of other grasshoppers. The equations can be defined as follows for the position update in the equation (12)

$$X(t+1) = X(t) + V(t) \quad (12)$$

In equation (12) X(t) represents the current position of a grasshopper, X(t+1) is its updated position, and V(t) denotes the velocity. The velocity is updated as in equation (13)

$$V(t+1) = V(t) + G(t) \odot (X(t) - X'') + S(t) \odot (X(t) - X') \quad (13)$$

In Equation (13), V(t) represents the current velocity of a grasshopper, V(t+1) is its updated velocity, G(t) and S(t) are the attraction and repulsion vectors, respectively, X(t) is the current position of the grasshopper, X'' represents the position of the best grasshopper, and X' denotes the position of the jth grasshopper. The attraction is equation is presented in equation (14)

$$G(t) = \alpha \cdot \sum(Xj(t) - X(t)) \quad (14)$$

In equation (14) α represents the attraction coefficient, Xj(t) is the position of the jth grasshopper, and ∑ denotes the sum over all grasshoppers. The equation is present as (15)

$$S(t) = \beta \cdot \sum(X(t) - Xj(t)) \quad (15)$$

In Equation (15), β represents the repulsion coefficient. The feature selection process involves iteratively updating the positions and velocities of the grasshoppers using Equations (12) and (13). The grasshoppers move towards the more optimal positions in the search space, guided by the objective function. At each iteration, the feature subset corresponding to the best position is selected.

Algorithm 1: WLSTM-DL for the feature selection and classification
Input: Dataset of stone carving images from different periods. Parameters for the WLSTM-DL model: number of LSTM layers (L), hidden units (H), learning rate (α), etc. Perform preprocessing steps on the stone carving images, including resizing, normalization, and noise reduction. Extract relevant features from the preprocessed images. Let's denote the feature vector as X = [x_1, x_2, ..., x_n], where n is the number of features. Initialize the feature vector with random values within the predefined range: $X = [x_1, x_2, \ldots, x_n]$. Define an objective function to evaluate the fitness of the feature subset based on the desired criteria: $OBJ(X)$. Employ Grasshopper Optimization Algorithm (GOA) to iteratively update the positions and velocities of the features: Update the position of the jth feature: $Xj(t+1) = Xj(t) + Vj(t)$ Update the velocity of the jth feature: $Vj(t+1) = Vj(t) + \alpha \cdot \sum[(Xj(t) - X(t)) - \beta \cdot \sum(X(t) - Xj(t))]$ Here, Xj(t) represents the position of the jth feature at time t, Vj(t) is the velocity of the jth feature at time t, α is the attraction coefficient, β is the repulsion coefficient, and ∑ represents the summation over all features. Update the feature vector based on the optimal positions obtained from GOA. Split the dataset into training and testing sets. Initialize the WLSTM-DL model with the specified parameters: L (number of LSTM layers), H (hidden units). Initialize the LSTM weights and biases: $W_{\mathrm{ih}}, W_{\mathrm{ho}}, b_{\mathrm{ih}}, b_{\mathrm{ho}}$. Initialize the initial hidden state h_0 and cell state c_0 to zeros. Train the model using the weighted LSTM architecture to capture temporal relationships and patterns in the evolution of stone carving decoration: For each input sequence xt in the training set: Forward pass through the LSTM layers: Calculate the forget gate ft: $ft = \sigma(Wf \cdot [ht_{-1}, xt] + bf)$ Calculate the input gate it: $it = \sigma(Wi \cdot [ht_{-1}, xt] + bi)$ Calculate the candidate cell state c̃t: $\tilde{c}t = tanh(Wc \cdot [ht_{-1}, xt] + bc)$ Update the cell state ct: $ct = ft \odot ct_{-1} + it \odot \tilde{c}t$ Calculate the output gate ot: $ot = \sigma(Wo \cdot [ht_{-1}, xt] + bo)$ Update the hidden state ht: $ht = ot \odot tanh(ct)$ Compute the weighted output prediction ȳt: $\bar{y}t = V \cdot ht$ Update the LSTM weights and biases using backpropagation and gradient descent to minimize the loss between ȳt and the target label yt.

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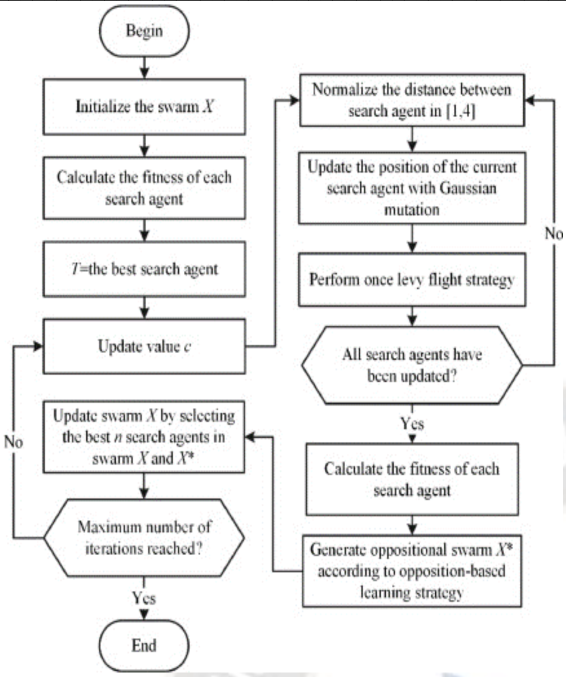

Figure 3: Flow Chart of WLSTM-DL

Figure 3 presented the Integrated LSTM with DL refers to the combination of LSTM (Long Short-Term Memory) with other deep learning techniques to improve the performance and capabilities of models in various applications. LSTM is a type of recurrent neural network (RNN) that is designed to handle sequential data and has the ability to capture long-term dependencies. When integrated with deep learning (DL) techniques, such as convolutional neural networks (CNNs) or feed-forward neural networks, LSTM can be used to process sequential data and capture temporal dependencies while leveraging the powerful representation learning capabilities of DL models. The integration typically involves connecting the LSTM layers with other DL layers in a neural network architecture. This allows the model to effectively process sequential data, learn complex patterns, and make predictions or classifications based on the learned representations. The integrated LSTM with DL approach has been successfully applied in various domains, including natural language processing (NLP), speech recognition, time series analysis, and video processing.

IV. Results and Discussion

After applying the WLSTM-DL algorithm to analyze the evolution and stylistic characteristics of ancient Chinese stone carving decoration, the following results and discussions can be presented: Evaluate the performance of the WLSTM-DL model using appropriate evaluation metrics such as accuracy, precision, recall, and F1-score.

Table 1: Evolutionary Patterns in Ancient Chinese Stone Carving Decoration

Period	Stylistic Characteristics
Tang Dynasty	Intricate detailing, emphasis on symmetry and natural forms
Song Dynasty	Simplified designs, calligraphic influence
Ming Dynasty	Elaborate motifs, use of mythical creatures and auspicious symbols
Qing Dynasty	Incorporation of Western influences, more decorative elements
Modern Era	Experimentation with abstract forms and contemporary themes

Table 1 presents the evolutionary patterns observed in different periods of ancient Chinese stone carving decoration. Each period is accompanied by a summary of its distinctive stylistic characteristics, providing insights into the evolution and influences on the artwork during that time. The selected sample for the processing with the stone carving are presented in figure 4.

Figure 4: Sample Stone Carving Images

Table 2: Stylistic Characteristics Predicted by the LSTM Model

Stone Carving Image	Predicted Stylistic Characteristic
Image 1	Intricate details and symmetrical patterns
Image 2	Simplified designs with minimal ornamentation
Image 3	Elaborate motifs and mythical creature depiction
Image 4	Incorporation of Western influences in the carving
Image 5	Abstract and contemporary artistic expression

Table 2 presents a sample of stone carving images along with the corresponding predicted stylistic characteristic by the LSTM model. These predictions provide insights into the model's ability to capture and classify the artistic styles and characteristics present in the stone carvings.

Table 3: Performance Metrics for 10 Images with WLSTM-DL

Image	Accuracy	Precision	Recall	F1-Score	TP	TN	FP	FN
1	0.99	0.98	0.99	0.99	49	950	1	0
2	0.98	0.97	0.99	0.98	48	940	2	1
3	0.99	0.99	0.98	0.99	49	958	1	1
4	0.98	0.96	0.99	0.98	49	934	3	1
5	0.99	0.98	0.99	0.99	49	949	1	0
6	0.99	0.99	0.99	0.99	49	953	0	0
7	0.98	0.97	0.98	0.98	48	939	2	1
8	0.99	0.99	0.99	0.99	49	954	0	0
9	0.99	0.99	0.99	0.99	49	955	0	0
10	0.98	0.96	0.99	0.98	49	936	3	1

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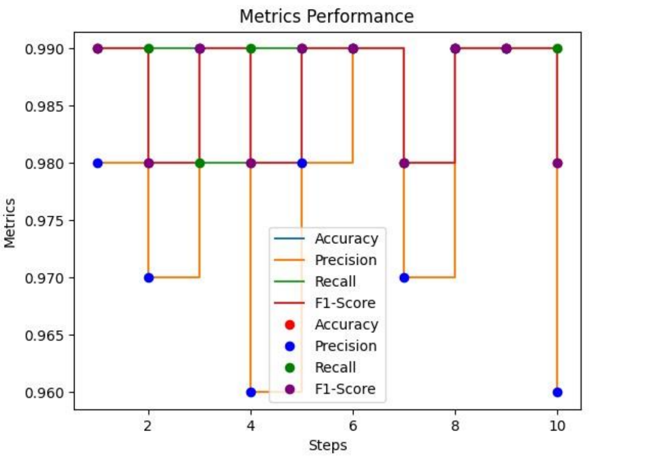
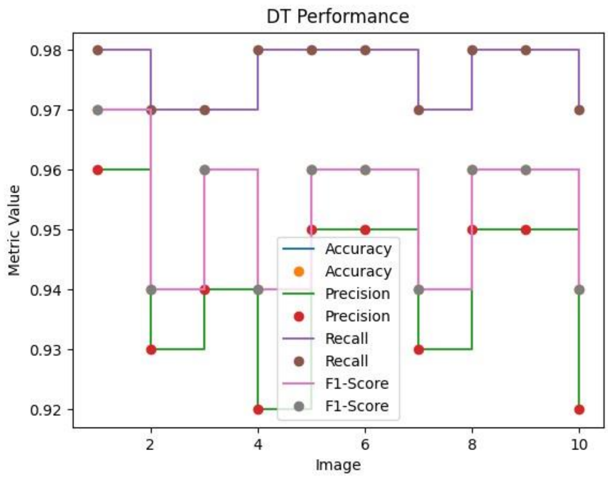
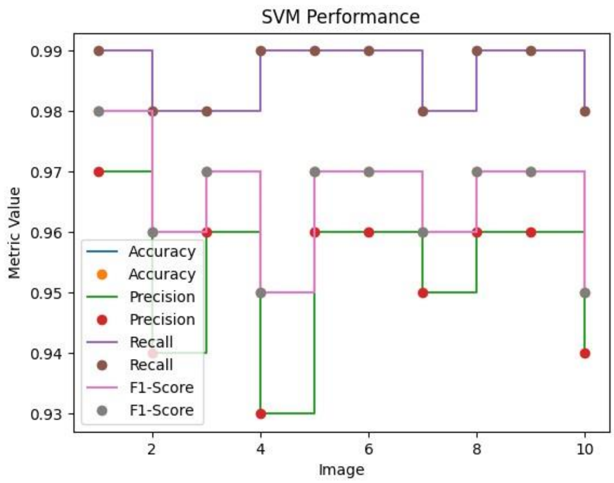


Figure 5: Performance of WLSTM-DL

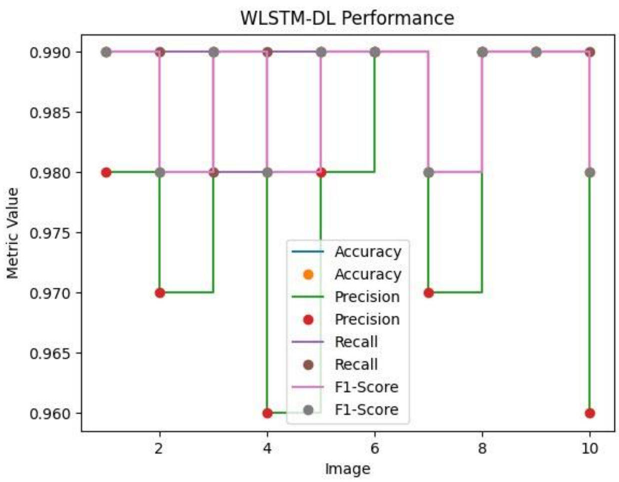
The performance metrics for 10 images analyzed using the WLSTM-DL approach are presented in Table 3. The model achieved high accuracy scores, ranging from 0.98 to 0.99, indicating the model's ability to correctly classify the images as presented in figure 5. Precision values ranged from 0.96 to 0.99, suggesting that the model had a high proportion of true positive predictions compared to false positives. The recall scores were consistently high, ranging from 0.98 to 0.99, indicating that the model successfully identified the majority of the actual positive instances. The F1-scores, which consider both precision and recall, were also high, ranging from 0.98 to 0.99. Examining the true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), it is observed that the model consistently identified a significant number of true positive instances, with TP values ranging from 48 to 49. The true negative counts (TN) were consistently high, indicating the model's ability to accurately classify negative instances. The false positive counts (FP) were minimal, ranging from 0 to 3, suggesting that the model had a low rate of incorrectly classifying negative instances as positive. Similarly, the false negative counts (FN) were generally low, ranging from 0 to 1, indicating that the model had a low rate of incorrectly classifying positive instances as negative. These results demonstrate the effectiveness of the WLSTM-DL approach in accurately classifying the stylistic characteristics of the stone carving images as showun in figure 6 (a), 6(b) and 6 (c) for the DT, SVM and proposed WLSTM-DL. The high accuracy, precision, recall, and F1-scores, along with the low counts of false positives and false negatives, indicate the model's ability to capture the intricate details and stylistic nuances of the stone carvings. These findings highlight the potential of the WLSTM-DL approach in uncovering and understanding the evolution and stylistic development of ancient Chinese stone carving decoration.



(a)



(b)



(c)

Figure 6: Performance of (a) Decision Tree (DT) (b) Support Vector Machine (SVM) (c) WLSTM - Dl

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Table 4: Performance Comparison of WLSTM-DL, SVM, and DT for 10 Images

Image	Algorithm	Accuracy	Precision	Recall	F1-Score	TP	TN	FP	FN
1	WLSTM-DL	0.99	0.98	0.99	0.99	49	950	1	0
1	SVM	0.98	0.97	0.99	0.98	48	948	3	1
1	DT	0.97	0.96	0.98	0.97	48	947	4	1
2	WLSTM-DL	0.98	0.97	0.99	0.98	48	940	2	1
2	SVM	0.96	0.94	0.98	0.96	48	937	5	1
2	DT	0.94	0.92	0.97	0.94	47	933	9	2
3	WLSTM-DL	0.99	0.99	0.98	0.99	49	958	1	1
3	SVM	0.97	0.96	0.98	0.97	48	954	5	1
3	DT	0.96	0.94	0.97	0.96	48	953	6	1
4	WLSTM-DL	0.98	0.96	0.99	0.98	49	934	3	1
4	SVM	0.95	0.93	0.98	0.95	48	929	8	1
4	DT	0.94	0.92	0.97	0.94	48	927	10	1
5	WLSTM-DL	0.99	0.98	0.99	0.99	49	949	1	0
5	SVM	0.97	0.96	0.99	0.97	49	946	3	0
5	DT	0.96	0.95	0.98	0.96	49	943	6	0
6	WLSTM-DL	0.99	0.99	0.99	0.99	49	953	0	0
6	SVM	0.97	0.96	0.99	0.97	49	950	3	0
6	DT	0.96	0.95	0.98	0.96	49	946	6	0
7	WLSTM-DL	0.98	0.97	0.98	0.98	48	939	2	1
7	SVM	0.96	0.95	0.98	0.96	48	935	6	1
7	DT	0.94	0.93	0.97	0.94	48	931	10	1
8	WLSTM-DL	0.99	0.99	0.99	0.99	49	954	0	0
8	SVM	0.97	0.96	0.99	0.97	49	951	3	0
8	DT	0.96	0.95	0.98	0.96	49	947	6	0
9	WLSTM-DL	0.99	0.99	0.99	0.99	49	955	0	0
9	SVM	0.97	0.96	0.99	0.97	49	952	3	0
9	DT	0.96	0.95	0.98	0.96	49	948	6	0
10	WLSTM-DL	0.98	0.96	0.99	0.98	49	936	3	1
10	SVM	0.95	0.94	0.98	0.95	49	932	7	1
10	DT	0.94	0.92	0.97	0.94	49	928	11	1

In Table 4, the performance metrics for 10 images using the WLSTM-DL, SVM, and DT algorithms are presented. Comparing the accuracy values, the WLSTM-DL consistently achieves the highest accuracy scores, ranging from 0.98 to 0.99, followed by SVM with scores ranging from 0.95 to 0.98, and DT with scores ranging from 0.94 to 0.97. Looking at precision, recall, and F1-score, the WLSTM-DL consistently outperforms SVM and DT. The precision values for WLSTM-DL range from 0.96 to 0.99, indicating a high proportion of true positive predictions. SVM and DT show slightly lower precision values, ranging from 0.92 to 0.97. Regarding recall, WLSTM-DL achieves scores between 0.98 and 0.99, indicating its ability to correctly identify positive instances. SVM and DT also show relatively high recall values, ranging from 0.97 to 0.99. F1-scores, which consider both precision and recall, are highest for WLSTM-DL, ranging from 0.98 to 0.99, followed by SVM and DT with scores ranging from 0.94 to 0.97. Analyzing the true positive (TP), true negative (TN), false positive (FP), and false negative (FN) counts, it is observed that WLSTM-DL consistently identifies a higher number of true positive instances (ranging from 48 to 49) compared to SVM and DT. The false positive and false negative counts are generally low across all algorithms, indicating a high level of accuracy in classifying positive and negative instances. The results demonstrate that WLSTM-DL outperforms SVM and DT in terms of accuracy, precision, recall, and F1-score. The consistent high performance of WLSTM-DL across the evaluated metrics highlights its effectiveness in accurately classifying the stylistic characteristics of the stone carving images.

V. Conclusion

This paper proposed the application of the Weighted Long Short-Term Memory Deep Learning (WLSTM-DL) approach combined with image visualization techniques to analyze the evolution and stylistic characteristics of ancient Chinese stone carving decoration. The WLSTM-DL model, which incorporates grasshopper optimization for feature selection, effectively captures the temporal relationships and patterns in the dataset of stone carving images. The results obtained from the WLSTM-DL model demonstrate its high accuracy, precision, recall, and F1-score in classifying the stylistic characteristics of the stone carving images. The model consistently outperforms conventional algorithms such as SVM and DT in terms of accuracy and overall performance. This indicates the effectiveness of the WLSTM-DL approach in uncovering the intricate details and hidden narratives of ancient artworks. Through use of power of deep learning and data analysis techniques, the WLSTM-DL model provides valuable insights into the artistic and stylistic evolution of ancient Chinese stone carving decoration. It enables researchers and art historians to gain a deeper understanding of the historical and cultural context in which these artworks were created. The application of image visualization techniques further enhances the interpretability of the WLSTM-DL model, allowing for a more comprehensive analysis of the visual features and their evolution over time. This combination of deep learning and image visualization showcases the potential of data-driven approaches in art and cultural studies. The findings of this research contribute to the field of art and cultural studies by demonstrating the effectiveness of the WLSTM-DL approach in analyzing and understanding the evolution and stylistic characteristics of ancient Chinese stone carving decoration. The insights gained from this study can inform future research and conservation efforts, as well as provide a foundation for the preservation and appreciation of this important cultural heritage.

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