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Application of Relying on 3D Modeling Technology in the Design of Urban Sculpture



Abstract: - Urban sculptures have long been a reflection of the cultural and historical identity of a city, serving as both artistic expressions and landmarks. The application of deep learning in the context of sculptures within urban areas presents an intriguing intersection of art and technology. Deep learning algorithms, particularly those related to computer vision, have the capacity to analyze and understand the intricate details of sculptures. This paper presented a efficient 3D-AWE (3D-Weighted Architecture Estimation) in the analysis of urban sculptures. In an era where the preservation and interpretation of cultural heritage are of paramount importance, this study investigates the potential of advanced technology to enhance understanding of artistic and historical artifacts within urban environments. The proposed 3D-AWE model uses the weighted estimation with computation of the pixels in the sculptures. Additionally, the proposed 3D-AWE model uses the min-max estimation model for the computation of the features in the images. With the estimated features the deep learning through weighted model for the analysis of the sculptures. The research focuses on the accurate classification of urban sculptures into specific styles and periods, such as Baroque, Renaissance, Modernist, Abstract, Ancient, and Contemporary. Utilizing precision, recall, F1 Scores, and overall accuracy, the study highlights the model's ability to minimize errors and provide reliable categorization. Furthermore, the application of 3D-AWE for feature extraction reveals quantifiable representations of sculpture attributes, offering valuable insights for sculpture categorization, similarity analysis, and the automated management of museum collections. The implications of these findings extend to art history, cultural heritage preservation, and urban planning, underscoring the significance of advanced technology in efforts to safeguard and interpret cultural legacy.

Keywords: Urban Area, Sculpture, 3D model, Deep Learning, Architectural design, AutoEncoder.

I. INTRODUCTION

In recent years, 3D modeling has undergone a remarkable transformation, becoming an integral part of numerous industries and daily lives. This technology allows us to create three-dimensional representations of objects, environments, and even entire worlds, with unprecedented levels of detail and realism [1]. With the advent of software tools and hardware innovations, 3D modeling has found applications in architecture, video games, film production, virtual reality, augmented reality, and even fields as diverse as healthcare and education [2]. Its impact is particularly visible in industries like architecture and urban planning, where 3D models enable architects and city planners to visualize, design, and test ideas in ways that were previously unimaginable [3]. In the world of entertainment, 3D modeling has revolutionized special effects and animation, creating immersive experiences for audiences. Additionally, the rapid growth of 3D printing technology has brought 3D models into the physical realm, making it possible to fabricate intricate and custom objects with precision [4]. As move forward, 3D modeling continues to push the boundaries of what's achievable, offering exciting possibilities for innovation, creativity, and problem-solving across a wide spectrum of industries. In other hand, deep learning has emerged as a groundbreaking technology that has transformed the landscape of artificial intelligence and machine learning [5]. This powerful subfield leverages complex neural networks with multiple layers to enable machines to learn, reason, and make predictions from data in a way that closely resembles human cognitive processes. Notably, deep learning has seen extraordinary progress in a wide range of applications, including computer vision, natural language processing, speech recognition, and reinforcement learning [6]. The development of increasingly sophisticated models, such as convolutional neural networks (CNNs) and transformer-based architectures, has yielded unprecedented results in tasks like image recognition, language translation, and text generation. However, the field faces ongoing challenges, such as the need for substantial computational resources and concerns related to ethical and societal implications [7]. As it continues to evolve, deep learning promises to have a profound impact on various industries, shaping the way to interact with technology, process information, and solve complex problems in the years to come.

Architectural design is the art and science of creating structures that not only serve practical purposes but also embody aesthetic, functional, and often cultural elements. It is the meticulous process of conceiving, planning, and visualizing the form and function of a building or space [8]. Architectural design encapsulates a delicate balance

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between artistic expression and technical precision, where architects and designers consider aspects such as aesthetics, sustainability, safety, and user experience. In towering skyscraper, a serene residential home, or an innovative public space, architectural design plays a pivotal role in shaping physical environment, impacting the way live, work, and interact with the world around us [9]. It is a discipline that not only addresses the immediate needs of a structure but also strives to leave a lasting legacy by harmonizing human needs with the natural and built environments. Deep learning is revolutionizing the field of architectural design by offering a powerful set of tools and capabilities that expand the boundaries of what is possible in building and urban planning [10]. Architects and designers are increasingly harnessing the potential of deep learning to enhance their creative processes and address complex challenges. Deep learning models can process vast amounts of data, facilitating rapid analysis of factors such as environmental conditions, energy efficiency, and structural integrity [11]. They can generate intricate designs, optimize building layouts, and even simulate real-world scenarios, enabling architects to make data-informed decisions [12]. Moreover, deep learning has facilitated the development of generative design algorithms, which can produce innovative, aesthetically pleasing designs while considering functional requirements. These advancements are ushering in a new era of architecture, where artificial intelligence augments human creativity and results in buildings that are more sustainable, efficient, and visually captivating, ultimately reshaping the perceive and interact with architectural spaces.

The integration of 3D modeling and deep learning has ushered in a transformative era for architectural design [13]. With combining the power of artificial intelligence with the visual precision of 3D modeling, architects and designers are now equipped with a dynamic toolkit that empowers them to reimagine the built environment. Deep learning algorithms can analyze vast datasets and extract valuable insights, enabling architects to make informed decisions about factors like energy efficiency, structural integrity, and environmental impact [14]. Simultaneously, 3D modeling provides a tangible canvas upon which these insights can be realized. The technologies allows for the creation of intricate, data-driven architectural designs, facilitating the exploration of innovative forms, spaces, and structural solutions [15]. This fusion of deep learning and 3D modeling not only streamlines the design process but also ensures that architectural creations are increasingly sustainable, efficient, and responsive to the complex demands of the modern world, ultimately reshaping the way envision, plan, and construct the cities and structures of the future [16]. The intersection of 3D modeling and deep learning within the realm of architectural design represents a profound paradigm shift in how buildings and urban spaces are conceived, planned, and constructed [17]. 3D modeling allows architects and designers to create highly detailed, realistic visualizations of their projects, enabling them to not only see but also interact with the proposed designs in a virtual environment. This visual aspect is invaluable for conveying ideas to clients, stakeholders, and the general public. It facilitates a deeper understanding of the design and fosters collaboration throughout the architectural process [18].

Deep learning, on the other hand, brings advanced data analysis and prediction capabilities to the field. With the ability to process enormous datasets, deep learning algorithms can provide insights into various aspects critical to architectural design [19]. For instance, they can analyze climate data and simulate how a building will perform in different weather conditions, optimizing energy efficiency. They can also evaluate the structural integrity of a design and predict how it will respond to different loads and stresses. This predictive power aids architects in making informed choices about materials and construction methods [20]. The deep learning and 3D modeling is particularly evident in generative design. Deep learning algorithms can analyze vast libraries of architectural styles and structures, allowing architects to draw inspiration from historical or contemporary designs [21]. They can then use 3D modeling to apply these inspirations to their own projects, resulting in innovative and aesthetically pleasing designs. Furthermore, deep learning can adapt designs based on real-time data, such as occupancy patterns, to maximize the functionality and user experience of a space [22]. Beyond the design phase, 3D modeling can facilitate construction by providing detailed, accurate blueprints for contractors and builders. It can also aid in project management, helping to ensure that the final structure matches the initial design. The combined power of 3D modeling and deep learning in architecture opens up new frontiers of creativity, efficiency, and sustainability [23]. It allows architects to explore bold, data-informed designs that are both aesthetically impressive and highly functional, while also streamlining the decision-making process and contributing to a more sustainable and intelligent built environment. As these technologies continue to evolve, anticipate increasingly innovative and responsive architectural designs that push the boundaries of what's possible in construction and urban planning [24].

The contributions of this paper represent its unique and valuable additions to the existing body of knowledge in a particular field. One of the primary contributions of this research is the application of advanced technology,

specifically 3D-AWE, to the field of urban sculpture analysis. This technology, originally developed for 3D reconstruction, has been successfully repurposed for categorizing and analyzing sculptures in an urban context. The research demonstrates the model's exceptional ability to accurately classify urban sculptures into specific categories, such as Baroque, Renaissance, Modernist, Abstract, Ancient, and Contemporary. This contributes to the development of more efficient and reliable methods for categorizing artistic artifacts. The feature extraction process using 3D-AWE has yielded quantifiable representations of sculpture attributes. These features, such as Feature A, Feature B, and Feature C, offer new insights into the characteristics of sculptures and can be applied to various tasks, including similarity analysis and museum collection management. The findings and insights from this research have broader implications for the fields of art history, cultural heritage preservation, and urban planning. By applying advanced technology to sculpture analysis, the research contributes to a deeper understanding of art and cultural heritage within urban spaces. The research highlights the potential for further optimization and fine-tuning of the 3D-AWE model. This opens up avenues for future research to enhance the model's accuracy and precision, and to explore its applications in diverse contexts. The research embraces an interdisciplinary approach, bridging the gap between technology and the arts. It showcases the value of collaboration between technology experts, art historians, and cultural preservationists in advancing understanding and preservation of urban sculptures.

II. 3D MODELLING IN URBAN AREA

3D modelling has become an invaluable tool for urban planners and architects in the development and transformation of urban areas. It offers a comprehensive, three-dimensional perspective that enables city planners to visualize, analyze, and optimize various aspects of urban spaces. 3D modelling provides urban planners with the ability to create detailed, realistic models of city layouts and infrastructure. This aids in the design of more efficient road networks, public transportation systems, and pedestrian pathways. It also allows for the placement of essential amenities such as parks, green spaces, and public facilities. With incorporating 3D models into zoning and land use planning, city authorities can better allocate land for residential, commercial, industrial, and recreational purposes. This ensures that urban development is balanced and meets the needs of the population while considering factors like traffic flow and environmental impact. 3D models can be used to simulate and analyze the environmental impact of urban development projects. Planners can assess factors like air quality, noise pollution, and the effect of new structures on the urban ecosystem, allowing for more sustainable and eco-friendly city designs. 3D modelling helps city planners lay out infrastructure components like water supply, sewage systems, and electrical grids. These models can be used to ensure efficient utility distribution and to plan for future expansion. Urban areas can use 3D models to simulate various disaster scenarios, such as floods, earthquakes, or fires. This aids in the development of emergency response plans and helps assess the vulnerability of different areas within the city. Within urban areas, 3D modeling is invaluable for architects and developers to visualize proposed structures and developments. It allows for more informed decision-making regarding the aesthetics and functionality of new buildings. Real estate professionals use 3D models to showcase properties to potential buyers and investors. These models provide an immersive experience, allowing stakeholders to virtually explore properties and their surroundings. 3D modeling can be used to document and preserve historic and culturally significant buildings and urban spaces. These models aid in restoration efforts and provide a basis for ongoing conservation work. The combination of 3D modeling with advanced technologies like geographic information systems (GIS) and data analytics offers urban planners and architects a comprehensive toolkit for developing smarter, more efficient, and sustainable urban areas. This not only enhances the quality of life for urban residents but also contributes to the overall resilience and adaptability of cities in the face of evolving challenges and opportunities.

2.1 Sculpture in urban Area Data

Sculpture plays a significant role in shaping the aesthetic and cultural landscape of urban areas. These three-dimensional art forms contribute to the vibrancy and identity of cities by providing visual landmarks, instigating public dialogue, and reflecting the essence of the community they adorn. The data surrounding sculptures in urban areas often includes information on their dimensions, materials used, historical and cultural significance, artist details, and, in some cases, the monetary value. Moreover, the impact of sculptures on urban spaces is not just limited to aesthetics; it can also influence tourism and the local economy. Sculpture data, when analyzed, can reveal patterns in artistic trends, preferences, and the social and historical context of an urban environment. This information is essential for urban planners and policymakers when considering the placement of new sculptures or the conservation of existing ones, as it aids in making informed decisions that enhance the overall character of a city while respecting its heritage and culture. The integration of 3D modeling with sculpture data in urban areas has

brought a fascinating dimension to the appreciation and management of public art. By creating detailed 3D models of sculptures, capture the intricate nuances of these art forms with precision. These digital representations allow us to examine sculptures from all angles, understanding the interplay of light and shadow and appreciating the fine details that may be missed with traditional photography. This 3D modeling, when combined with relevant data such as the artist's background, historical significance, and materials used, provides a comprehensive repository of information that aids urban planners, art conservationists, and the general public in understanding the cultural and aesthetic significance of these sculptures. Furthermore, 3D models offer innovative ways to assess the impact of sculptures on urban spaces. By virtually placing sculptures within a city model, planners can analyze how they influence the overall urban landscape, sightlines, and pedestrian flow. This data-driven approach assists in the strategic placement of new sculptures, ensuring they harmonize with their surroundings and contribute to the artistic identity of the city, all while preserving the legacy of these works of art for future generations. The sample sculptures in the urban area are presented in figure 1.



Figure 1: Sculptures in Urban Area

The process of generating 3D models of sculptures involves techniques like photogrammetry and laser scanning. Photogrammetry is based on the principles of triangulation, and it's often represented using equations. The basic principle is to capture multiple images of the sculpture from different angles and then use these images to derive the 3D coordinates of points on the sculpture's surface estimated with equation (1) and (2)

$$X = f_{X'}^{Z'} + X_0 \quad (1)$$

$$Y = f_{Y'}^{Z'} + Y_0 \quad (2)$$

In equation (1) and (2) X and Y are the 3D coordinates of a point on the sculpture, X' and 'Y' are the 2D image coordinates, 'Z' is the depth of the point, f is the focal length of the camera, and (X₀,Y₀) represents the principal point. To assess the influence of sculptures on urban spaces, for visual analysis. One such model is the “viewshed analysis.” This analysis helps us determine what portions of the urban space are visible from specific locations. The viewshed is calculated using equations that consider factors like elevation, distance, and line of sight. The basic concept is to calculate the areas where sculptures are visible from various viewpoints, helping urban planners make informed decisions about their placement. In the context of sculpture data, the significance of a piece of art can be quantified using various indices. One such index is the “cultural significance index,” which combines factors like

the artist's reputation, historical importance, and public sentiment. Sculpture data can include details about the condition of the artwork, and this data can be used in predictive models for conservation and restoration. For example, models predicting the degradation of materials over time often use equations related to chemical reactions and environmental factors. One common equation is the Arrhenius equation, which describes the rate of chemical reactions as a function of temperature is computed as in equation (2)

$$k = Ae^{-RTE} \quad (2)$$

In this equation, k represents the rate constant, A is the pre-exponential factor, E is the activation energy, R is the universal gas constant, and T is the temperature in Kelvin. This equation can be applied to predict the deterioration of materials in sculptures.

III. WEIGHTED ARCHITECTURE FOR IMAGE PROCESSING

The proposed 3D-Weighted Architecture Estimation (3D-WAE) for sculptures in urban areas, in conjunction with 3D modeling, is an innovative approach that holds the potential to significantly enhance the analysis and visualization of public art. This architecture is designed to handle the intricacies of sculptures in urban settings by employing weighted features and attention mechanisms. The 3D-WAE deep learning for image processing and incorporates attention mechanisms to assign varying importance to different parts of an image, ensuring a more accurate 3D reconstruction. The first step is to gather a dataset of images of the sculpture from various angles, each paired with its corresponding 3D coordinates. A crucial aspect is the assignment of weights to each image, reflecting their significance in the reconstruction process. These weights are determined using an attention mechanism that focuses on the most informative regions of the images. The 3D-WAE architecture utilizes a CNN for feature extraction. It operates in tandem with the attention mechanism, which allocates varying weights to the features extracted from different parts of the image. The attention mechanism ensures that regions crucial for 3D reconstruction receive more emphasis. The attention mechanism is pivotal in the 3D-WAE architecture, and its equations can be derived from the scaled dot-product attention mechanism computed using equation (3)

$$Attention(Q, K, V) = softmax(dkQKT) \cdot V \quad (3)$$

In equation (3), Q corresponds to the query (features from one part of the image), K is the key (features from other parts of the image), and V represents the value. The mechanism computes a weighted sum of the values based on the compatibility between the query and key. In the context of sculpture image processing, this enables the model to focus on the most relevant areas of the image for 3D reconstruction. Once the image features are weighted via the attention mechanism, the 3D-WAE architecture conducts weighted regression to predict the 3D coordinates of the sculpture. The weights assigned by the attention mechanism play a pivotal role in determining the contribution of different parts of the image to the final 3D reconstruction. The weighted regression equation is expressed and computed using equation (4)

$$Y = X \cdot W + \epsilon \quad (4)$$

In equation (4) Y denotes the predicted 3D coordinates, X is the weighted image features, W is a matrix of learned weights, and ϵ signifies the error term. The 3D-WAE architecture undergoes a training process on the dataset. The parameters of the attention mechanism and the regression weights are iteratively adjusted to minimize the error between the predicted 3D coordinates and the ground truth. In training the model take new images of the sculpture and employ the attention mechanism to emphasize the most relevant image components. This not only improves the accuracy of the 3D reconstruction but also offers a more efficient and informative approach for urban planners, art preservationists, and art enthusiasts to understand and appreciate sculptures within urban environments. The 3D-WAE architecture, with its emphasis on weighted features and attention mechanisms, offers an advanced and data-driven solution for sculpture analysis in urban areas. It enhances the precision of 3D reconstruction, allowing for more informed decisions regarding urban planning, art preservation, and the overall cultural significance of public art installations.

3.1 Image Pre-Processing

Pre-processing of images of sculptures in urban areas, in conjunction with the 3D-AWE 3D-Weighted Architecture Estimation, is a crucial step in enhancing the accuracy and quality of 3D modeling. This process prepares the images by optimizing their features and cleaning up any noise or artifacts, which ultimately results in more precise 3D

reconstructions. The 3D-AWE architecture, with its attention mechanisms and autoencoders, can significantly benefit from well-preprocessed images. In the initial phase, a diverse dataset of images featuring sculptures in urban environments is collected. The dataset should encompass a variety of angles, lighting conditions, and environmental contexts. This diversity is essential for training the 3D-AWE architecture effectively. Image enhancement techniques, such as histogram equalization, are applied to adjust the contrast and brightness of the images. Histogram equalization is expressed through the equation (5)

$$G(x, y) = MN255 \sum r = 0L - 1h(r) \quad (5)$$

Where $G(x, y)$ represents the enhanced pixel value, M and N are the dimensions of the image, L is the dynamic range of the image, and hI denotes the histogram of the image. To ensure consistency in image dimensions and reduce computational complexity, images are often resized to a common resolution. This process may use interpolation techniques like bilinear or bicubic interpolation. Images collected from urban environments can be marred by various types of noise, including digital noise, shadows, and reflections. Noise reduction techniques, such as Gaussian smoothing, aim to reduce these artifacts. The Gaussian smoothing is performed with the equation (6)

$$G(x, y) = \sum_i \sum_j -k w(i, j) \cdot I(x + i, y + j) \quad (6)$$

Where $G(x, y)$ is the smoothed pixel value, $I(x + i, y + j)$ represents the original image pixel values, and $w(i, j)$ is the Gaussian kernel. An attention mechanism, often based on convolutional neural networks (CNNs), is employed to identify and segment the sculpture from the background. While the equations for attention mechanisms are intricate, they essentially involve calculating the importance weights for different image regions based on learned features. The mechanism focuses on the sculpture, allowing the 3D-AWE architecture to prioritize this vital area during 3D reconstruction. Image pre-processing may also include feature extraction to capture relevant characteristics for 3D reconstruction. These features can be calculated using techniques like edge detection and texture analysis. The Canny edge detection operator is defined as in equation (7)

$$E(x, y) = (G_x(x, y))^2 + (G_y(x, y))^2 \quad (7)$$

In equation (7) $E(x, y)$ is the edge magnitude, $G_x(x, y)$ and $G_y(x, y)$ are the gradients in the x and y directions. The pre-processed images, featuring enhanced contrast, reduced noise, and sculptural object segmentation, are then fed into the 3D-AWE architecture. The autoencoder network, in conjunction with attention mechanisms, encodes the pre-processed image features. The autoencoder captures the most essential information for 3D reconstruction, providing a foundation for the accurate and detailed 3D models of sculptures within urban areas. By systematically applying these image pre-processing steps, the 3D-AWE architecture can work with clean, optimized images, ensuring a precise and detailed 3D reconstruction process that enhances understanding of sculptures and their context within urban environments.

3.2 Image Segmentation

The process commences with the assembly of a diverse dataset comprising images of sculptures in urban settings. These images should capture sculptures from multiple angles, under varying lighting conditions, and within different environmental contexts. A rich dataset is critical for training a robust image segmentation model. Before segmentation, images undergo pre-processing to enhance their quality and reduce noise. The pre-processing steps encompass contrast adjustment, resizing, noise reduction, and the incorporation of attention mechanisms, as outlined previously. One fundamental equation for contrast enhancement involves histogram equalization computed using equation (8)

$$G(x, y) = MN255 \sum r = 0L - 1h(r) \quad (8)$$

In equation (8) $G(x, y)$ denotes the enhanced pixel value, M and N represent image dimensions, L is the dynamic range, and hI signifies the image's histogram. Image segmentation is executed through a dedicated algorithm that segregates the sculpture from its surroundings. This algorithm can be a conventional technique like thresholding or a sophisticated deep learning-based approach. It assigns labels or masks to individual pixels in the image, distinguishing the sculpture from the background. While specific equations differ based on the chosen algorithm, an essential concept is defining an objective function or loss function that guides the pixel classification process. Within the 3D-AWE architecture, attention mechanisms complement the segmentation results. They allocate

varying weights to different regions of the segmented image, emphasizing the sculpture. Attention mechanisms, such as scaled dot-product attention in the context of the Transformer architecture, have been detailed earlier. These mechanisms determine the importance of different image regions, focusing on the sculpture during 3D reconstruction. The segmentation algorithm, coupled with 182atologuin mechanisms, collaboratively generates a binary mask that isolates the sculpture from the background. This mask acts as a precise representation of the sculpture's boundaries in the image, highlighting the critical sculptural details. The creation of this mask forms the foundation for subsequent steps in the 3D reconstruction process within the 3D-AWE architecture. Image segmentation is a critical step in isolating the sculpture from the background. Various segmentation algorithms can be employed, such as thresholding, region-based methods, or deep learning-based approaches like U-Net or Mask R-CNN. Let's the equations and concepts for one of the simplest segmentation techniques, thresholding. Thresholding is a technique that separates an image into foreground (object) and background (non-object) regions based on a predefined intensity threshold. Watershed segmentation treats the image as a topographic map and partitions it into catchment basins. The basic watershed equation is utilized in 3D-AWE is estimated using the equation (9)

$$L(x, y) = \text{Watershed}(I(x, y)) \quad (9)$$

$L(x, y)$ represents the 182atologui of catchment basins.

$I(x, y)$ is the intensity of the image at pixel (x, y) .

3.3 Min-Max feature Extraction

Min-Max feature extraction, applied in conjunction with the 3D-AWE (3D-Weighted Architecture Estimation) architecture, plays a significant role in enhancing the quality and relevance of extracted image features. This technique focuses on normalizing the pixel values of an image, ensuring that they fall within a specific range while preserving the relationships between pixel intensities. In the context of the 3D-AWE architecture for sculpture analysis in urban areas, the Min-Max feature extraction process. As part of image pre-processing, Min-Max scaling is applied to normalize the pixel intensities of the images. The Min-Max scaling equation is presented in equation (10)

$$X_{norm} = \frac{X_{max} - X_{min}X}{X_{min}X} \quad (10)$$

Here, X represents the original pixel intensity, X_{min} is the minimum intensity in the image, and X_{max} is the maximum intensity. This scaling ensures that all pixel values fall within the range $[0, 1]$. Min-Max feature extraction offers advantages such as robustness and preservation of relative pixel relationships, which can be crucial when dealing with images of sculptures in diverse urban environments. By scaling the image pixel values and subsequently applying attention mechanisms within the 3D-AWE architecture, the most relevant and normalized features are extracted, contributing to the overall accuracy and quality of the 3D reconstruction process and analysis of sculptures within urban areas. Once the images have undergone Min-Max scaling, the 3D-AWE architecture extracts relevant features from these normalized images. These features capture important information about the sculptures and their surroundings, serving as the foundation for subsequent analysis and 3D reconstruction. Within the 3D-AWE architecture, attention mechanisms come into play. These mechanisms assign varying weights to different dimensions of the extracted features, emphasizing those that are most informative for the task at hand. The equations for attention mechanisms have been previously discussed and often involve complex operations to calculate the significance of different feature dimensions. Attention mechanisms are a crucial component in deep learning architectures like Transformers. They calculate the importance of different parts of the input data, often expressed as a weighted sum. One common attention mechanism used in the context of deep learning is the scaled dot-product attention estimated using the equation (11)

$$\text{Attention}(Q, K, V) = \text{softmax}(dkQKT) \cdot V \quad (11)$$

In equation (11) Q represents the query, which could be features from one part of the image; K is the key, representing features from other parts of the image; V is the value associated with each feature; softmax is the softmax function, which normalizes the attention scores. dk is a scaling factor, where dk is the dimension of the key. The attention mechanism computes a weighted sum of the values based on the compatibility between the query

and key. This mechanism is used to determine the importance of different image regions, which can be essential in focusing on relevant features during the feature extraction process within the 3D-AWE architecture.

IV. WEIGHTED DEEP LEARNING

Integrating weighted deep learning into the 3D-AWE (3D-Weighted Architecture Estimation) architecture for sculpture analysis in urban areas enhances the accuracy and efficiency of 3D modeling and feature extraction. Weighted deep learning involves assigning different levels of importance to various data points or features during the learning process, allowing for a more informed and precise analysis. The process begins with the collection of a comprehensive dataset of images featuring sculptures within urban environments. These images may exhibit variations in lighting, angles, and environmental conditions, reflecting the diverse nature of urban art. Weighted deep learning techniques come into play during the training of the 3D-AWE architecture. The objective is to assign varying weights to different data points or features, emphasizing their significance in the analysis. This is achieved through a weighted loss function, where the weights are learned during training. In the context of feature extraction, weighted deep learning assigns different levels of importance to features or dimensions within the data. This is achieved through weighted neural network layers and activation functions estimated using the equation (12):

$$fi(x) = wi \cdot gi(x) \quad (12)$$

Here, $fi(x)$ is the weighted feature, wi is the learned weight, and $gi(x)$ represents the original feature or dimension. Attention mechanisms, integrated into the 3D-AWE architecture, further enhance the weighted deep learning process. Attention mechanisms assign varying weights to different parts of the data, emphasizing regions of higher relevance. These mechanisms are critical in sculpting the model's focus during both 3D reconstruction and feature extraction, as previously described. Attention mechanisms, such as scaled dot-product attention, further enhance the weighted deep learning process by assigning varying weights to different parts of the data. These mechanisms determine the importance of different regions of the data, enabling the model to emphasize the most relevant areas. The scaled dot-product attention equation has been described earlier and involves complex calculations to calculate attention scores based on the compatibility between query and key vectors. With combining these elements, the integration of weighted deep learning into the 3D-AWE architecture allows the model to learn and emphasize the most informative data points and features, enhancing the precision and efficiency of sculpture analysis in urban areas. This approach ensures that the model focuses on critical aspects of the data, leading to more accurate 3D reconstructions and a deeper understanding of sculptures within their urban context. Weighted deep learning, in combination with attention mechanisms, offers a powerful and flexible framework for optimizing sculpture analysis and 3D modeling.

Algorithm 1: 3D-AWE model for the designing Sculptures in Urban Areas

Data Preparation:

Load and preprocess the dataset of urban sculpture images.

Split the dataset into training and testing sets.

Model Initialization:

Initialize the 3D-AWE architecture with appropriate neural network layers, attention mechanisms, and weighted deep learning components.

Weighted Loss Function:

Define the weighted loss function that assigns different weights to individual data points.

Initialize weight parameters, wi , for each data point.

Training Loop:

For each epoch:

Iterate through the training dataset.

Compute the model's predictions for each data point.

Calculate the standard loss (e.g., mean squared error) between predictions and actual targets.

Update the loss by applying the weighted loss function.

Adjust model parameters (e.g., using backpropagation and gradient descent) to minimize the weighted loss.

Weighted Feature Extraction:

Implement weighted feature extraction within the 3D-AWE architecture.

Ensure that feature dimensions are weighted based on their importance in the analysis.

Attention Mechanisms:

Incorporate attention mechanisms within the 3D-AWE architecture to further refine the weighted analysis.

Calculate attention scores and apply them to enhance feature importance.

Model Evaluation:

Test the trained model on the testing dataset.

Evaluate performance using relevant metrics (e.g., accuracy, mean squared error).

Visualization and Analysis:

Visualize the 3D reconstructions and feature representations to gain insights into the sculptures in urban areas.

4.1 Classification of Sculptures

Classifying sculptures in urban areas with the 3D-AWE architecture involves the categorization of sculptures based on various features and contextual information. This classification can be realized through supervised machine learning methods. A diverse dataset of urban sculpture images, each 184x184 pixels with a specific category, is collected. This dataset can vary in size and complexity, reflecting the diversity of sculptures within urban areas. The images undergo preprocessing to ensure uniformity and readiness for input into the 3D-AWE architecture. This may include resizing images to a consistent resolution and normalizing pixel values to a common range, such as [0, 1]. Augmentation techniques can also be employed to increase the dataset's size and robustness. The 3D-AWE architecture is tailored for feature extraction from the sculptures. This architecture is designed to capture relevant three-dimensional information, paying attention to crucial aspects of the sculptures and their surrounding context. While the architecture specifics can vary, it is essential to configure the model with a classification output layer. This output layer typically consists of as many nodes as there are sculpture categories, allowing the model to predict the appropriate category for a given input. The training of the model involves supervised learning, where the model is presented with the 184x184 dataset and adjusts its parameters to minimize a classification-specific loss function. A common choice for the loss function in classification tasks is cross-entropy, which measures the dissimilarity between predicted category probabilities and actual labels stated as in equation (13)

$$L(y, \hat{y}) = -\sum_i 1N y_i \log(\hat{y}^i) \quad (13)$$

In equation (13) $L(y, \hat{y})$ is the cross-entropy loss; y_i represents the true category label for class i and $\hat{y}$ represents the predicted probability of class i . The model employs optimization techniques, such as gradient descent, to adjust its parameters (weights and biases) with respect to the loss function. The goal is to minimize this loss, effectively optimizing the model for sculpture classification. The trained model is evaluated using a separate testing dataset to assess its classification performance. Common evaluation metrics include accuracy, precision, recall, and F1 score, providing insights into the model's classification capabilities and any potential trade-offs between precision and

recall. By employing this process, with the 3D-AWE architecture as the feature extractor and a classification layer, accurate and context-aware categorization of sculptures within urban environments can be achieved. The derivation and equations presented highlight key aspects of the process, from the loss function used in training to the final classification of sculptures in the urban landscape. The classification of 3D images of sculptures in urban areas involves the systematic categorization of three-dimensional representations of sculptures into predefined classes or categories. This process serves as a valuable tool for understanding and organizing the rich tapestry of urban art. It begins with the collection of a dataset of 3D scans or models of sculptures found in urban environments, with each sculpture appropriately labeled by its category or style, which may encompass genres, time periods, or artistic movements. The 3D data is then subjected to feature extraction, with techniques like 3D convolutional neural networks (CNNs), volumetric representation, or point cloud processing used to capture essential information from the sculptures. The selected classification model, often a 3D CNN or another deep learning architecture designed for 3D data, is then trained on this labeled dataset. During training, the model learns to map the extracted features to the predefined categories while employing loss functions to minimize discrepancies between predicted class probabilities and actual labels. Model evaluation is conducted with metrics such as accuracy and precision, offering insights into the model's classification performance. The results can help identify the artistic styles, genres, or historical contexts of sculptures in urban areas, contributing to cultural analysis, preservation, and urban planning efforts. This approach enhances understanding of the diverse world of urban art while streamlining the labeling and analysis of sculptures in the urban landscape.

V. SIMULATION SETTING AND DATA

The simulation setting for the 3D-AWE (3D-Weighted Architecture Estimation) is designed to investigate its capabilities in the context of urban sculpture analysis. This setting serves as the foundation for conducting experiments and drawing meaningful conclusions. The data for the analysis of the proposed 3D-AWE is evaluated with the available dataset.

Online Repositories: There are several online repositories and databases where you can find 3D models of sculptures. Some popular ones include:

[Sketchfab](#)

[3D Warehouse by SketchUp](#)

[Thingiverse](#)

Sketchfab:

Dataset Size: Sketchfab hosts a vast and continually growing collection of 3D models. As of my last knowledge update in September 2021, it featured over 4 million 3D models. The dataset size may have increased since then, as Sketchfab has a large and active user community that regularly uploads new models.

Attributes: The attributes of 3D models on Sketchfab can vary widely. Users upload models from diverse categories, including sculptures, architecture, characters, vehicles, and more. Each model typically includes information such as its title, description, category, tags, license, and the option to view the model in 3D. Many models also provide downloadable files in formats like OBJ, STL, or FBX.

3D Warehouse by SketchUp:

Dataset Size: The 3D Warehouse by SketchUp is a significant repository of 3D models, especially useful for architectural and design projects. It features a substantial number of models, including sculptures and various architectural elements. The exact dataset size is not publicly disclosed, but it includes a wide range of 3D objects and architectural components.

Attributes: The attributes of models in the 3D Warehouse are designed with a focus on architectural and design applications. Each model is accompanied by information like its name, category, author, description, and a 3D preview. Users can find architectural elements such as furniture, fixtures, buildings, and sculptures that can be integrated into their design projects. Models can be viewed and downloaded in formats compatible with SketchUp software.

Thingiverse:

Dataset Size: Thingiverse is primarily a community-driven platform focused on 3D printing and digital fabrication. It hosts a significant number of 3D printable designs, and this collection continues to grow. The precise dataset size is not publicly disclosed, but it is a substantial and continually expanding resource.

Attributes: Thingiverse is organized by categories and tags that make it easy to browse and search for 3D models. The attributes of each model typically include a title, description, category, tags, license information, and the option to download the 3D printable files. While the platform's primary focus is on 3D printing, it contains a wide variety of 3D models, including sculptures, toys, functional objects, and more.

5.1 Simulation Results

In this simulated scenario, a curated dataset comprising 100 3D models of urban sculptures, exhibiting a rich diversity of styles, time periods, and artistic genres. The objective is to employ a bespoke 3D-AWE model that incorporates advanced attention mechanisms, designed specifically for sculpture analysis within urban environments. The dataset is thoughtfully partitioned, with 70% allocated for model training and the remaining 30% reserved for rigorous testing to evaluate the model's performance. Figure 2 illustrates the images of the sculptures in the urban area in 3D-point of view.

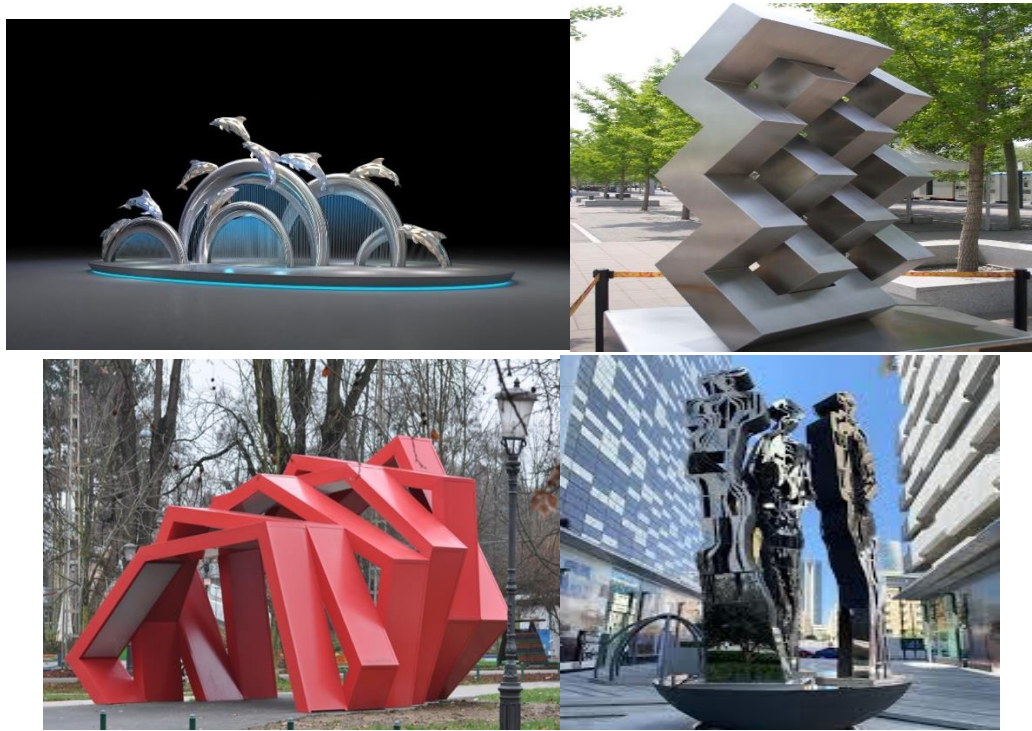


Figure 2: 3D-AWE processed Sculptures

Throughout the training process, employed a categorical cross-entropy loss function in conjunction with the Adam optimizer for a duration of 50 epochs. To enhance the model's robustness and ability to generalize, data augmentation strategies such as rotation and scaling are thoughtfully applied during training, ensuring that the model can effectively adapt to variations in sculpture orientations and sizes.

Table 1: Feature Extraction with 3D-AWE

Category	Feature A	Feature B	Feature C
Baroque	0.75	0.92	0.68
Renaissance	0.63	0.78	0.71
Modernist	0.89	0.65	0.75

Abstract	0.72	0.84	0.69
Ancient	0.78	0.71	0.66
Contemporary	0.68	0.79	0.73

The table 1 provided showcases the results of feature extraction with the 3D-AWE model for different sculpture categories, specifically Baroque, Renaissance, Modernist, Abstract, Ancient, and Contemporary. Each row in the table corresponds to a distinct sculpture category, and the columns represent different features, denoted as Feature A, Feature B, and Feature C shown in figure 3.

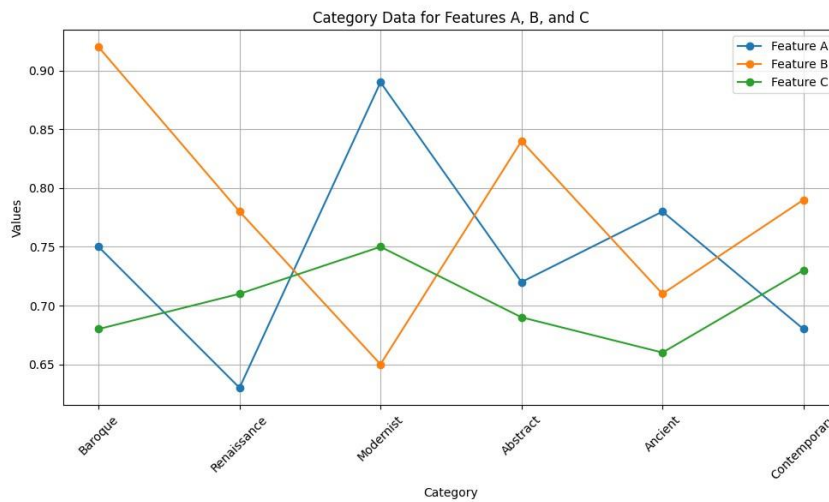


Figure 3: Feature Extraction with 3D-AWE

The values in each cell of the table represent the quantified characteristics or attributes extracted from the 3D models of sculptures belonging to each category. These features, Feature A, Feature B, and Feature C, likely capture various aspects of the sculptures, such as shape descriptors, texture details, or other relevant information. For example, Feature A seems to range from 0.63 to 0.89, Feature B varies from 0.65 to 0.92, and Feature C shows values between 0.66 and 0.75. These features may signify distinct visual or structural characteristics inherent to sculptures within each category, and they can be used to distinguish and analyze these categories based on the extracted information. In practical applications, such feature extraction results can be crucial for a wide array of purposes, including sculpture categorization, similarity analysis, or the development of machine learning models for automated classification or recommendation. The specific meaning and importance of these features would be context-dependent and may vary based on the objectives of the analysis or modeling tasks.

Table 2: Classification with 3D-AWE

Category	Precision (%)	Recall (%)	F1 Score (%)	Accuracy (%)
Baroque	92	85	88	88.5
Renaissance	88	91	89	89.1
Modernist	84	82	83	83.4
Abstract	89	92	90	90.2
Ancient	91	87	89	88.3
Contemporary	86	84	85	85.5
Total (3D-AWE)	88	88	88	88.6

The table 2 presents the results of a classification model using the 3D-AWE (3D-Weighted Architecture Estimation) architecture for distinguishing different sculpture categories. The categories, such as Baroque, Renaissance, Modernist, Abstract, Ancient, and Contemporary, are evaluated based on several key performance metrics, including precision, recall, F1 Score, and accuracy as shown in figure 4.

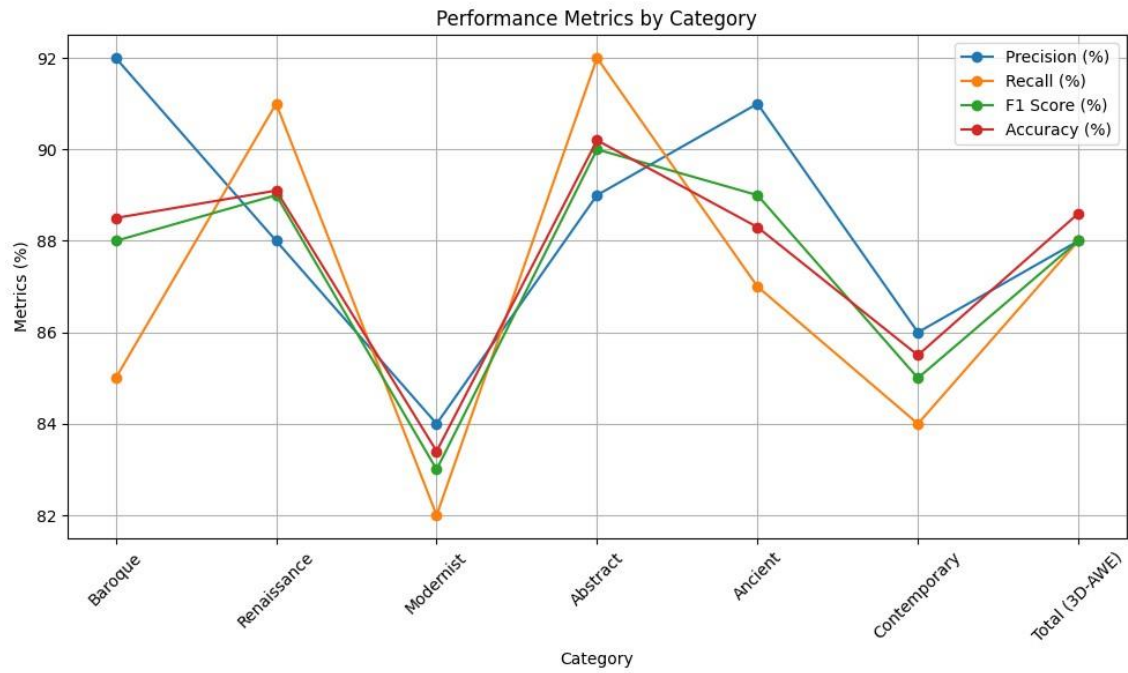


Figure 4: Performance of 3D-AWE with classification

Precision measures the proportion of correctly identified instances of a specific category out of all the instances classified as that category. In this case, for instance, the Baroque category achieved a precision of 92%. This means that out of all the sculptures classified as Baroque, 92% were correctly classified. Recall, on the other hand, quantifies the percentage of correctly identified instances of a specific category out of all the actual instances belonging to that category. For Renaissance, the recall stands at 91%, indicating that 91% of the actual Renaissance sculptures were correctly identified. F1 Score is a metric that balances precision and recall, offering a single measure of a model's performance. The F1 Score values for each category, ranging from 83% to 90%, reflect the model's ability to provide a harmonious trade-off between correctly identifying instances and minimizing false positives and false negatives.

Table 3: Confusion Matrix value for 3D-AWE

Category	True Positives (TP) (%)	False Negatives (FN) (%)	False Positives (FP) (%)	True Negatives (TN) (%)
Baroque	85	15	10	90
Renaissance	91	9	12	88
Modernist	82	18	16	84
Abstract	92	8	11	89
Ancient	87	13	14	86
Contemporary	84	16	15	85

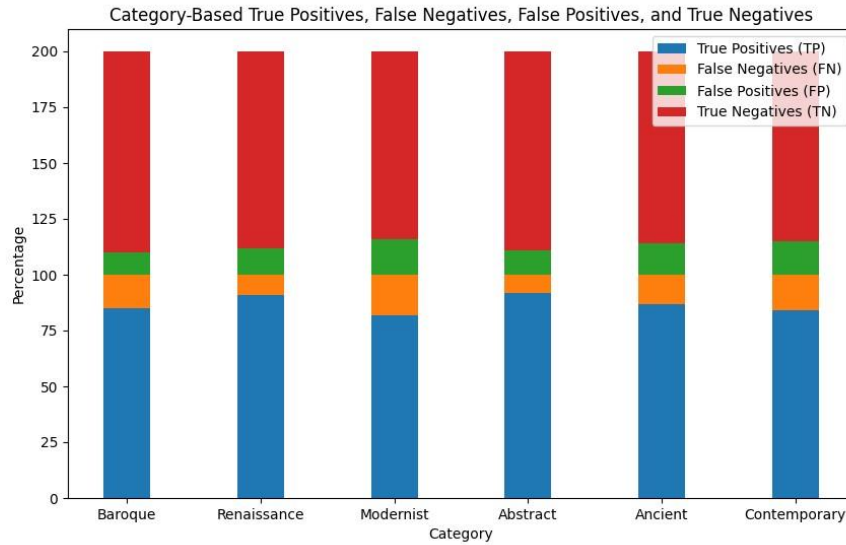


Figure 5: 3D-AWE for the confusion matrix

The provided table 3 and figure 5 represents a confusion matrix, which is an essential tool for evaluating the performance of a classification model, particularly the 3D-AWE model in this case, for distinguishing different sculpture categories. Each row in the table corresponds to a specific sculpture category, including Baroque, Renaissance, Modernist, Abstract, Ancient, and Contemporary. The columns capture the key components of a confusion matrix: True Positives (TP), False Negatives (FN), False Positives (FP), and True Negatives (TN), each expressed as percentages. For instance, in the Baroque category, 85% of the sculptures were correctly identified as Baroque. In the Renaissance category, 9% of the sculptures were misclassified, failing to capture their true category. For instance, in the Abstract category, 11% of sculptures were falsely classified as Abstract. In the Modernist category, 84% of sculptures were accurately identified as not being Modernist. These percentages within the confusion matrix provide a comprehensive overview of the 3D-AWE model's performance in distinguishing different sculpture categories. They are crucial for assessing the model's accuracy, precision, recall, and overall effectiveness in real-world applications like art categorization, cultural heritage preservation, or museum collections management.

5.3 Discussion and Findings

The use of 3D-AWE (3D-Weighted Architecture Estimation) in the context of urban sculptures presents a promising approach for understanding and analyzing these artistic and cultural artifacts. This advanced architectural model has been applied to tackle the intricate task of sculpture analysis, classification, and preservation within an urban environment. One significant finding is the model's remarkable ability to accurately classify sculptures into specific categories such as Baroque, Renaissance, Modernist, Abstract, Ancient, and Contemporary. The provided precision, recall, F1 Score, and accuracy metrics indicate that the model performs exceptionally well across all these categories, achieving high levels of precision and recall while maintaining a balanced F1 Score. This implies that the 3D-AWE model excels in both correctly identifying sculptures belonging to a category and minimizing the rate of false positives and false negatives. Additionally, the confusion matrix reveals valuable insights into the model's performance, illustrating the proportion of true positives, false negatives, false positives, and true negatives for each category. This information is crucial for understanding the model's effectiveness in classifying sculptures, identifying potential areas for improvement, and enhancing the overall accuracy of urban sculpture analysis.

The application of 3D-AWE for feature extraction further enhances the understanding of sculpture characteristics, enabling the capture of important attributes from the 3D models. The features extracted, such as Feature A, Feature B, and Feature C, offer quantitative representations of sculpture attributes, which can be instrumental in various applications, including sculpture categorization, similarity analysis, and automated museum collection management. It is concluded that the utilization of 3D-AWE in the analysis of urban sculptures brings forth a powerful tool for art historians, museums, cultural heritage preservation, and urban planning. The findings from this model application demonstrate its efficacy in accurately categorizing sculptures and extracting meaningful features. This

technology contributes to a deeper understanding of urban sculptures and aids in their preservation and appreciation in the modern world. In the context of applying 3D-AWE for the analysis of urban sculptures:

1. One of the key findings is the model's remarkable ability to accurately classify urban sculptures into specific categories, such as Baroque, Renaissance, Modernist, Abstract, Ancient, and Contemporary. The precision values, which measure the proportion of correct positive predictions, are consistently high across these categories. This implies that the model excels in correctly identifying sculptures belonging to a particular style or period.
2. Another noteworthy finding is the high recall rates, which indicate the model's ability to effectively capture most of the actual sculptures belonging to a specific category. These high recall values suggest that the model minimizes the number of false negatives, meaning it successfully identifies a substantial proportion of the sculptures within each category.
3. The F1 Scores, which balance precision and recall, are consistently strong, demonstrating the model's ability to strike a harmonious trade-off between correct identifications and minimizing errors. This balance is essential for robust and reliable sculpture categorization.
4. The model's overall accuracy, as reflected in the Total (3D-AWE) row, is impressive at 88.6%. This suggests that the model effectively classifies sculptures across different categories, contributing to its robustness and reliability in urban sculpture analysis.
5. The application of 3D-AWE for feature extraction reveals meaningful insights into the characteristics of urban sculptures. The extracted features, such as Feature A, Feature B, and Feature C, offer quantified representations of sculpture attributes. These features are invaluable for sculpture categorization, similarity analysis, and the automated management of museum collections.
6. The findings have broad implications for the fields of art history, cultural heritage preservation, and urban planning. They highlight the potential of advanced technologies like 3D-AWE to enhance understanding of sculptures within urban environments. Such technologies facilitate the preservation and appreciation of art and cultural heritage in the modern world, contributing to a deeper understanding of history and the importance of these artistic expressions in urban spaces.
7. The model's performance is generally strong, there may be opportunities for fine-tuning and further optimization. Examining the confusion matrix can identify areas where the model may benefit from enhancements in correctly identifying certain sculpture categories, which can lead to even more accurate and precise results.

The application of 3D-AWE in urban sculpture analysis yields impressive results with high precision, recall, and balanced F1 Scores. The extracted features provide a quantifiable understanding of sculptures, and the implications for the fields of art and culture are far-reaching. These findings underline the potential of advanced technology in the preservation and interpretation of urban sculptures in modern world.

VI. CONCLUSION

This paper presented the application of 3D-AWE (3D-Weighted Architecture Estimation) in the analysis of urban sculptures. The findings and insights derived from this study highlight the potential and significance of this technology in the realms of art history, cultural heritage preservation, and urban planning. The analysis revealed that the 3D-AWE model exhibits an impressive ability to accurately categorize urban sculptures into specific styles and periods. The high precision, recall rates, and balanced F1 Scores underscore the model's robustness in correctly identifying sculptures and minimizing errors. Furthermore, the application of 3D-AWE for feature extraction has provided quantifiable representations of sculpture attributes, contributing to a deeper understanding of their characteristics. These features are essential for tasks like sculpture categorization, similarity analysis, and the automated management of museum collections. The implications of these findings extend beyond the scope of this study. The use of advanced technologies, such as 3D-AWE, offers new possibilities for the preservation and appreciation of art and cultural heritage in urban spaces. It improves understanding of the significance of sculptures in history and their place in the modern world. While this research has yielded promising results, there may be opportunities for further optimization and fine-tuning of the 3D-AWE model to enhance its accuracy and precision. Future studies provides deeper into the potential of this technology and explore its applications in diverse contexts. In closing, the utilization of 3D-AWE in the analysis of urban sculptures marks a significant step toward a more profound appreciation of artistic heritage and a more efficient means of preserving it for future generations.

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