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RESEARCH ON MODELLING ARCHITECTURAL HERITAGE OF THIRD-LINE CONSTRUCTION BASED ON HIERARCHICAL ANALYSIS AND DATA FUSION USING RAT SWARM TUNED ARTIFICIAL NEURAL NETWORK

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Abstract. This study explores the novel use of Artificial Neural Networks (ANNs) with Rat Swarm Optimization (ANN-RSO) to model the architectural legacy of third-line construction projects. A multi-layered, combined approach to thoroughly assess and protect valuable historical buildings is constructed by the study through the application of hierarchical analysis and data fusion tools. The approach makes use of ANN-RSO power to maximize the analysis and understanding of a variety of data sets, from historical and cultural relevance to structural details and material compositions. Through the systematic division of complicated data into digestible layers, hierarchical analysis improves the neural network's power by concentrating on distinct aspects at various levels. Data fusion combines different data kinds at the same time, such as verbal descriptions, architectural plans, and photographic proof, to create a rich, consistent database that feeds into the neural network. By fine-tuning the ANN parameters, the RSO approach greatly increases the model's efficiency and accuracy in predicting and modeling architectural features. This study provides a standard for the use of modern computational techniques in the protection of cultural heritage in addition to showcasing the potential of ANN-RSO in architectural heritage modeling. The results show that these technologically advanced models can be essential resources for architectural historians and preservationists working on reconstruction projects, giving them a better understanding of the past and more precise reconstructions of historical buildings.

Key words: Architectural Heritage, Third-Line Construction, Hierarchical Analysis, Data Fusion, Rat Swarm Optimization, Artificial Neural Networks, Model Accuracy, Cultural Preservation

1. Introduction.

1.1. Importance of Protecting Cultural Heritage and Digital Preserving Technologies. Due to their historical, cultural, and educational significance, third-line constructions have to have their cultural heritage protected. These structures often denote important historical periods and capture the architectural styles, materials and techniques of their eras[6]. By keeping these buildings in active, future generations will be able to connect with their past in a tangible way and will be better able to understand and value their cultural identity. The conservation of architectural history now requires the use of digital preservation techniques. It is possible to produce accurate digital models of these historic structures using modern technology[17, 16]. These models fulfill two functions: they are essential for recording minute details that are subjected to erosion or destruction, and they act as a digital backup in case the actual structures are lost to time. These digital models are also very helpful for historical construction research and restoration[19]. Accurate restorations are made easier by their ability to undertake comprehensive assessments by architects and conservationists without compromising the quality of the original structures. These models can also simulate the results of various restoration treatments and environmental changes, which can assist decision-makers in more efficiently designing preservation plans[12, 8]. Digital models improve learning in educational settings by allowing experts and students to realistically study historical constructs. Learning becomes more accessible and engaging as a result, as these models may be shared worldwide across all physical and geographic barriers.

1.2. Previous Techniques under Preserving and its Limitations. The preservation of architectural heritage has always depended on physical restoration and traditional recording procedures, by considering the importance of heritage, these traditional techniques have significant drawbacks [3, 5]. Extensive physical

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involvement is a common component of traditional restoration, which can be demanding and occasionally result in the loss of original materials and designs. This can be a dangerous technique because structures with substantial historical value may be completely altered. While necessary, traditional documentation techniques like physical measurements and photos only provide a limited amount of detail and do not fully express the complex nature of architectural details. Additionally, these approaches produce stable records that are not suitable to active analysis and may be challenging to update[8, 10]. They can also disappear as a result of accidents, and they are capable of decay over time. Because of these restrictions, the dynamic and detailed elements of architectural history are not always completely preserved, which makes it difficult to carry out precise restorations or carry out in-depth historical study. These approaches are also inadequate in terms of accessibility, since conservation requirements and geographical limitations may restrict physical access to sites, which in turn restricts educational opportunities and wider public involvement with cultural heritage.

1.3. Machine Learning Involvement and its advantages. The field of architectural heritage preservation can benefit greatly from machine learning, mainly because of its capacity to accurately and efficiently handle vast amounts of difficult data. The improvement of condition monitoring and predictive maintenance is one major benefit. Through the analysis of data trends over time, machine learning algorithms are able to identify possible degradation and structural difficulties [18, 15, 2]. This allows for preventive interventions to prevent damage to historical structures. Furthermore, machine learning makes it easier to create large, advanced 3D models and simulations that accurately depict architectural elements. This feature is essential for the digital reconstruction of pieces that have been damaged because it allows researchers and to see and modify precise representations of the original structures without running the danger of additional physical interference. In addition, architectural styles and elements can be automatically classified by machine learning algorithms, which simplifies the documentation process and improves information management[11]. This technology provides extensive study of historical sites from distant locations, as well as improved accessibility and interactive learning opportunities. Overall, machine learning improves the global understanding and enjoyment of architectural history in addition to increasing the efficacy and efficiency of preservation efforts.

1.4. Proposed RSO-ANN and its advantages. By considering the modern technology development and its advantages in various applications, particularly AI and machine learning, this study, presents a new novel approach called ANN-RSO, Artificial Neural Network enabled Rat Swarm Optimization algorithm. In the field of cultural heritage preservation, the RSO-ANN is an innovative strategy that combines the advantages of neural networks and optimization approaches[7]. RSO is a well-known optimization algorithm that is effective in locating the best answers to challenging issues. It was inspired by the group behavior of rats. RSO efficiently modifies the weights and biases of a network to improve an ANN's accuracy and performance. When working with the difficult data of architectural heritage, where accuracy is critical, this improvement is especially important. Because RSO-ANN combines the optimization skills of RSO with ANN's capacity to model non-linear interactions, it is especially well-suited for producing digital models of historical constructions that are incredibly precise and accurate. Architectural features require exact details and patterns to be captured by these models in order to be analysed and restored. There are several benefits to using RSO-ANN for cultural heritage preservation. It can handle huge datasets with a variety of data kinds, increases prediction accuracy, and streamlines the modeling process overall. This eventually contributes to the ongoing appreciation and conservation of cultural heritage by improving preservation tactics, improving restoration choices, and deepening our understanding of historical architecture.

The difficulties presented by the many and intricate datasets related to architectural heritage—which range from intricate architectural drawings to transient historical texts and images—were the driving force behind this project. Conventional analytical techniques frequently fail to combine this diverse data into a logical, useful framework. Through the use of a combination of data fusion and hierarchical analysis methods, this study attempts to take advantage of the strong capabilities of ANN-RSO in order to efficiently analyze and comprehend these layered datasets. This approach intends to establish a new benchmark in the computational preservation of cultural assets, while simultaneously improving the depth and accuracy of architectural study.

2. Related Work. The combination of advanced computational tools and optimization strategies to improve the preservation and sustainable reuse of cultural material is a common theme across the previous works

Table 2.1: Previous studies Contributions in Cultural Heritage Preservation

Study	Source	Techniques Used	Improvements
[9]	Decision making for cultural heritage protection using Matlab and Python	Combined documentation protocols, advanced software programming, mathematical models for decision making	Easy to implement, expandable, compatible across different OS
[14]	Sustainable reuse of heritage buildings with Diva-grasshopper and Octopus plugin	Thermal and daylight simulation, multi-objective genetic optimization	Improved energy and daylight performance, tested and validated techniques
[1]	Priority setting in the conservation of Florence's old city center	Monitoring of degradation, optimization of construction costs, strategic planning within management plans	Harmonized with local plans, promotes cost-effective joint construction sites
[4]	Securing and repairing historical objects using FLAC2D	Structural, conservation, and architectural criteria (S-C-A method), Finite Difference Method for stability analysis	Applicable to various structures, aids in stabilizing historical sites

which is mentioned below. These studies highlight the value of data-driven decision-making, the applicability of these techniques to many types of heritage conservation projects, and the application of simulation and optimization for energy efficiency and structural stability. Additionally, they stress the significance of creative approaches and the necessity of compliance with current frameworks and systems for efficient management and preservation of cultural resources.

The current approaches for preserving architectural history frequently have trouble integrating and evaluating disparate data sources efficiently. Different processing strategies are needed for textual records, architectural plans, and photographic evidence. Many current models are unable to combine these disparate data sources into a cohesive analytical strategy. This may result in fragmented insights and the omission of important relationships.

The multi-layered complexity of data that is frequently encountered in architectural heritage projects is too much for many conventional and computational methods to handle. Methods without hierarchical analysis run the risk of overlooking important information that require more in-depth, structured data investigation to identify.

The current computational techniques may not be sufficiently scalable or computationally demanding for large-scale heritage projects with substantial datasets. Their practical application is limited by this constraint, particularly in resource-constrained conditions common to many preservation efforts. The models used to forecast and reconstruct architectural elements frequently differ significantly in terms of accuracy and precision. Errors in restoration due to modeling inaccuracies may cause irrevocable damage to priceless historical buildings.

3. Methodology.

3.1. Methodology General Outline. Several crucial elements are included in the proposed ANN-RSO technique for architectural heritage preservation in order to guarantee the accuracy and efficiency of the model. The process starts with data gathering, when several kinds of information about the architectural history are collected. Examples of this information include structural dimensions, material properties, historical context, and visual documentation. After that, this large dataset is pre-processed to standardize and normalize the data so that neural network processing may use it. After the data is prepared, the neural network's architecture is created, usually consisting of multiple layers that are arranged in a way that best captures the intricacies of the architectural data. Through the RSO process, which simulates rats' hunting behavior, this tuning is continuously improved in order to find the ideal set of parameters that reduce error and improve the model's predicted accuracy. The prepared dataset is then used to train the optimal neural network, allowing it to identify and recreate the complex patterns and features of the architectural history. Before used in real-world

Table 3.1: Dataset Features

Features	Details
Total Number of images	10,235
Training set size	8,188 images (80%)
Validation set size	2,047 images (20%)
Independent Test set size	1,404 images
Image Resolution	Original varied sizes, 128x128 pixels, 32x32 pixels, 64x64 pixels
Rescaling Method	Smaller dimension adjusted to 128 pixels, central region trimmed to 128x128 pixels
Dataset Availability	Publicly available on DataHub: DataHub Link
Source of Dataset Categories	Getty Art & Architecture Thesaurus (AAT)
Comparative Tests	Compared with another dataset of 5,000 images classified into 25 architectural styles from Wikimedia Commons

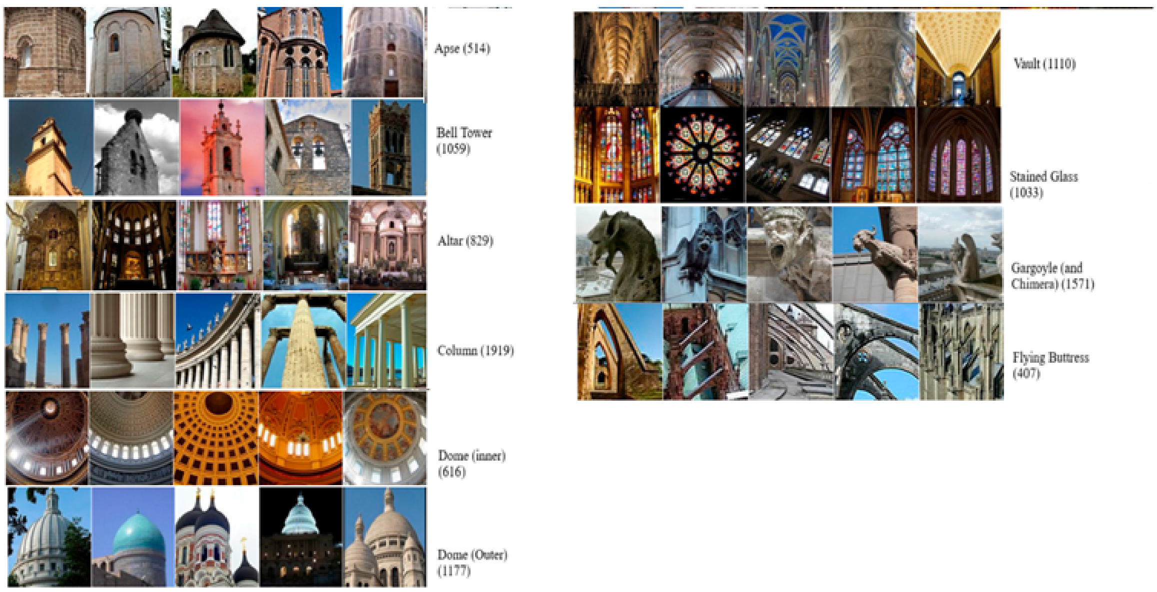

Fig. 3.1: Collected Image Samples

heritage preservation applications, the model is validated and tested after training to guarantee its accuracy and dependability. This approach makes use of ANN advantages in processing difficult, multi-dimensional data, and RSO guarantees that the network is running to its full potential. The end product is a reliable instrument for cultural heritage analysis and digital preservation.

3.2. Data Collection and Preprocessing. Several kinds of cultural heritage images are collected and are fed to pre-processing to make sure about its ability. The collected are normalized using preprocessing techniques to remove noise. Data collection process cover several kinds of images form the AHE dataset which is described below.

The collection of images from Architectural Heritage Elements (AHE)-Dataset is adapted from the study[13], the features of the adapted dataset are presented in Table 3.1, Figure 3.1 graphically depicts the collected images from AHE Dataset.

Careful data collection and preprocessing are required in the first phases of the ANN-RSO process since they are essential for the analysis that follows. Through the collection of several types of data, such as structural measurements, material attributes, historical context, and visual documentation, the model guarantees an extensive dataset that accurately represents the complex nature of architectural history. Standardization and normalization are two preparatory techniques that convert this heterogeneous input into a format that is ideal for neural network computation. This guarantees consistency between various forms of information and improves the quality of the data, both of which are critical for precise analysis.

3.3. Artificial Neuarl Network (ANN). Artificial Neural Networks (ANN) are parallel connectionist architectures developed to simulate the neural network of the human brain in order to solve difficult issues. ANN are composed of three layers: input, hidden, and output which is visually depicted in Figure 3.2. Neurons, which are complex mathematical processing units, make up each layer. Weights and biases connect the neurons, allowing information to move more easily throughout the network. Particularly, the research has shown that one hidden layer in the design is usually enough to handle a wide range of difficult functions.

We use a structured procedure with our ANN-RSO model for the protection of architectural heritage. The input layer receives data and transfers it to the hidden layer, where processing takes place. The hidden layer is essential because it uses an activation function and a combination of weights to process inputs.

$$H_{oj} = F_j \left(\sum_{i=1}^{r} iw_{j,i}\ x_i + hb_j \right) \tag{3.1}$$

is the computational formula for the hidden layer. The weight between input neuron i and hidden neuron j is represented by $iw_{j,i}$, the bias at the hidden layer is represented by hb_j, r is the total number of input neurons, the input data is represented by x_i, and the transfer function is represented by F. The output is computed at the output layer after the hidden layer, where the output of each neuron is given by

$$Y_k = F_k \left(\sum_{j=1}^{N} Hw_{k,j} H_{oj} + ob_k \right) \tag{3.2}$$

where $ob_k$is the bias in the output layer and $Hw_{k,j}$ represents the weight between hidden neuron j and output neuron k.

After the architecture of the ANN is established, training is done using input and output data sets that are known to provide the proper weights and biases for the network. Finding the ideal values for the weights and biases of the network is referred to as "network training." The right weights and biases for the ANN are usually found using a variety of methods. By varying the values of neural weights and biases, the unstructured optimization issue of ANN training is to reduce the global error. In order to come closer to the goal, a learning algorithm iteratively modifies the values of the network parameters for the input–output vector training data that is supplied. Usually, to carry out this update process, the error signal is back-propagated layer by layer, and the parameters are adjusted according to the error signal's magnitude. The most popular learning algorithm that has been developed is back-propagation, which has been successfully applied to represent a wide range of processes.

3.4. Rat Swarm Optimization Algorithm (RSO). A unique metaheuristic algorithm called RS) was developed after observing and attacking rats. Male and female rats live in swarms and are considered regional creatures. The rats can be very violent in many situations, which can lead to multiple animal deaths. Rats' aggressive and subsequent behaviors are mathematically modeled in this method to carry out optimization. The rat swarm optimizer begins with a set of random solutions that reflect the rat's position in the search space, just like the other population-based optimization methods. This random population is continuously calculated by an objective function and refined according to the aggressive and follower behaviors of rats. The initial positions of eligible solutions, or the positions of the rats, are chosen at random in the search space in the original RSO technique as follows

$$xi = xi\ min + rand \times (xi\ max - xi\ min),\ i = 1, 2, \ldots,\ N \tag{3.3}$$

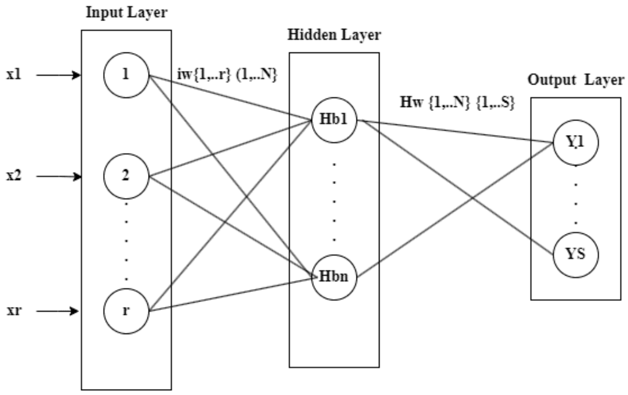

Fig. 3.2: ANN Architecture

where the lower and higher bounds of the ith variable are denoted, respectively, by $xi\ min$ and $xi\ max$. Rats typically follow the bait in a group by engaging in painful social behaviors. It is mathematically assumed that the best search agent is aware of where to place prey in order to explain the behavior of rats. As a result, the other search agents can share their positions based on the best search agent found thus far. It has been proposed that the rat's updated next position and the procedure by which it attacks with food are represented by

$$\overrightarrow{pi}\,(t+1) = |\overrightarrow{pr}\,(t) - \overrightarrow{p}\,| \tag{3.4}$$

where t is the number of iterations, $\overrightarrow{pi}\ (t)$ is the most optimal solution identified thus far, and $\overrightarrow{pi}\ (t+1)$ specifies the updated positions of ith rats.

$$\overrightarrow{p} = A \times \overrightarrow{pi}\,(t) + c \times (\overrightarrow{pr}\,(t) - \overrightarrow{pi}\,(t)) \tag{3.5}$$

where $\overrightarrow{pi}\,(t)$ defines the position of ith rats and the calculation of parameter A and C is expressed as follows

$$A = r - t \times \left(\frac{r}{tmax}\right), t = 1, 2, 3 \ldots, tmax \tag{3.6}$$

$$c = 2 \times rand \tag{3.7}$$

A random number between [1,5] and [0,2] makes up the parameter r. The parameter c is also random. The optimization process is currently in iteration t, and the maximum number of iterations is $tmax$. Equation (3.4) saves the optimal solution and updates the search agents' locations. While RSO outperforms other evolutionary algorithms such as Moth-fame Optimization (MFO), Grey Wolf Optimizer (GWO), and Gravitational Search Algorithm (GSA) in finding global optima, it may have issues finding optimal solutions when examining difficult functions. This study combines opposition-based learning (OBL) into an algorithm of RSO in order to improve the efficiency of RSO. RSO starts with a set of initial responses and works its way toward the best solution iteratively. Equation (3.3) generates random initializations without the need for prior solution knowledge

$$xi = rand\,[xi\ min,\ xi\ max] \tag{3.8}$$

Notably, when these initial solutions approach the optimal solution, better performance and faster convergence are usually attained. By using OBL, the MRSO algorithm produces an opposing number for every initial position, which could move the initial solutions closer to the global optimum.

$$X = (x1, x2, \ldots, xn) \tag{3.9}$$

is the definition of an N-dimensional vector X, where each xi lies inside a given range $[xi\ min, xi\ max]$,

$$\overrightarrow{xi} = (xi\ max + xi\ min) - xi\ ,\ i = 1, 2, \ldots,\ N \tag{3.10}$$

which states that $\overrightarrow{xi} = (xi\ max + xi\ min) - xi$, is used to determine xi, which is the opposite of xi. In RSO, the objective function $f(\cdot)$ evaluates both a random solution and its inverse (xi). $xi$is changed to $\overrightarrow{xi}$ if $F(\overrightarrow{xi}) < F(xi)$; this decision-making procedure is carried out on the first iteration to start the algorithm with more promising solutions. Like many algorithms, RSO may still converge to local conditions despite its efficiency. In order to overcome this, RSO uses another approach in which the least advantageous solution as defined by the goal function is expressed as

$$xworst = \begin{cases} rand1 \times \overrightarrow{pr}\ (t)\, if\ rand\ 3\ \leq 0.5 \\ (xi\ max + xi\ min) - xi\ if\ rand\ 3 > 0.5 \end{cases} \tag{3.11}$$

This technique promotes diversity and examines new areas inside the issue space by replacing the position of the least desirable rat with either a random new position based on the current best solution or its reverse.

Algorithm 1 Proposed RSO Algorithm

Define algorithm parameters: population size N, maximum iterations $t_{\max}$
for $i = 1$ to N **do**
  Initialize the positions of rat agents x_i using a culturally informed distribution method
  Evaluate the opposite positions of the rats $\overline{x}_i$ based on cultural metrics using Equation (3.10)
  if $\overline{x}_i < f(x_i)$ **then**
    Replace x_i with $\overline{x}_i$
  end if
end for
Initialize learning factors and coefficients A, c, and r
Identify and record the best search agent $\overline{P_r} \leftarrow$ best for heritage data
while $t < t_{\max}$ **do**
  for $i = 1$ to N **do**
    Update A and c adaptively for cultural context using Equations (3.6) and (3.7)
    Update the positions of rat agents x_i for cultural data using Equation (3.4)
    Evaluate the fitness of each rat agent with respect to heritage preservation
    if a rat agent reaches beyond predefined cultural constraints **then**
      Adjust its position
    end if
  end for
  Identify and replace the worst-performing rat agent with a new culturally feasible solution using Equation (3.11)
  Update the best search agent $\overrightarrow{p}_r$ if a better candidate is found
  $t = t + 1$
end while

When RSO's optimization skills are combined with ANN's proficiency in handling intricate, multidimensional data, a potent instrument for cultural heritage preservation is produced. This collaboration makes it possible to take a dynamic, flexible approach that not only addresses the unique requirements of architectural data analysis but also pushes the envelope in terms of what is possible for digital preservation and restoration. To sum up, the ANN-RSO strategy offers a strong, dependable, and effective way to examine and conserve architectural history. For architectural historians, preservationists, and anybody else concerned in the conservation of cultural heritage, it is an essential tool due to its capacity to manage intricate datasets and continuously optimize its performance.

4. Results and Experiments.

4.1. Evaluation Criteria. The accuracy and loss presented in Figure 4.1 and 4.2 for training and validation show the effectiveness of the ANN-RSO model. The training accuracy increases steadily over the course of

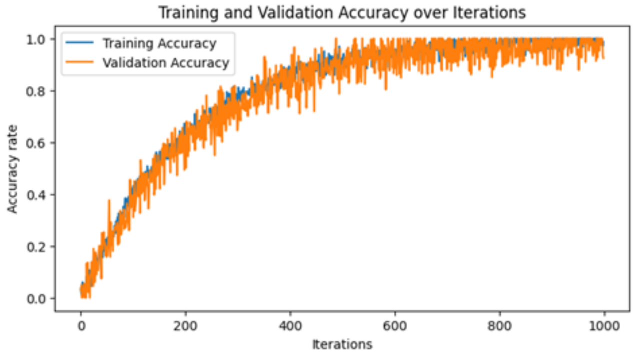

Fig. 4.1: Training and Validation Accuracy of tested samples

Fig. 4.2: Training and validation loss over samples

the iterations, gradually getting closer to a high degree of accuracy, showing the model's capacity to efficiently learn from the dataset. This is a positive sign that the RSO tuning mechanism and the model's design are capable of identifying the basic trends in the architectural heritage data. Concurrently, the trajectory of the validation accuracy shows a similar rising trend, while being significantly lower, indicating that the model has high adaptation skills when exposed to unknown data. When training and validation accuracy converge, the model is well-fitted and has minimal to no overfitting. The training and validation loss measurements show decreases with iterations in terms of loss, supporting the trends in accuracy. The model's effectiveness in reducing errors during the learning phase is demonstrated by a sharp drop in training loss. In the meantime, there is a noticeable decline in the validation loss in addition to a minor offset that suggests a greater error rate on the validation set. The relatively small difference between the validation and training losses supports the model's stability and its ability to function reliably in practical applications for the preservation of cultural assets. Together, these patterns show the way the ANN-RSO model learns intricate representations while preserving the reliability needed for accurate and reliable predictions in the field of architectural heritage.

An ANN-RSO model's learning trajectory through iterative training phases is shown in Figure 4.3 of Feature Matching Score. The model's feature matching performance initially begins at a lower baseline, showing that it is still in the early stages of learning and is only now starting to identify the distinctive features of the architectural heritage dataset. The capacity of the model to match features from the real heritage site with its digital reconstruction grows gradually with the number of iterations, showing a successful learning curve. The score shows some fluctuations, but overall, it is consistent with the expected training process of a deep learning model. Variability in the score can be caused by the algorithm's exploration of the solution space, the introduction of more difficult patterns in the dataset and variations in the quality of the data. In order to

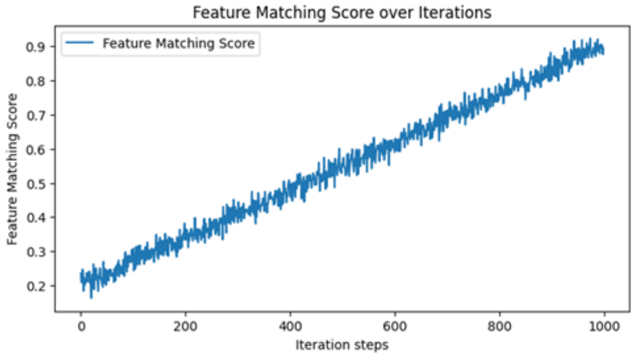

Fig. 4.3: Feature Matching Score

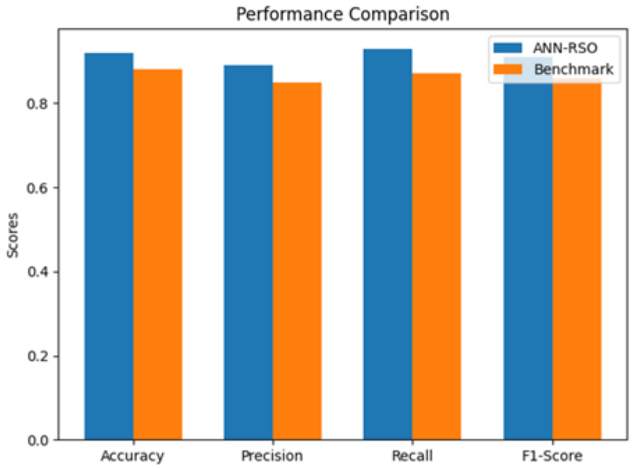

Fig. 4.4: Comparison Analysis

improve its feature matching skills, the model must balance discovering new patterns with taking advantage of established ones, as seen by the fluctuations. At the end the score shows the higher values marks the ANN-RSO effectiveness in adapting the architectural data.

Figure 4.4 shows the comparative effectiveness of the proposed ANN-RSO model, which highlights a significant improvement in performance over a number of important parameters. With a higher accuracy, the ANN-RSO model is able to identify a larger proportion of architectural historical characteristics properly, both in terms of their existence and absence. This is particularly important in the field of heritage preservation, since correct documentation and analysis depend on the precise identification of architectural features. With a precision metric that beats the benchmark, the ANN-RSO model is able to identify features with a greater percentage of true positives, demonstrating its capacity to reduce false positives and accurately recreate heritage sites. Additionally, the recall and F1-Scores also shows the highest scores when compared with the benchmarks.

5. Conclusion. With a focus on third-line construction projects, this study illustrates the creative use of ANN-RSO in the field of architectural heritage preservation. Through the incorporation of hierarchical analysis and data fusion methodologies, the study presents a strong methodological foundation for assessing and preserving historical structures. The application of ANN-RSO improves the examination of various datasets, covering topics ranging from structural compositions to cultural value, thereby promoting a more comprehensive comprehension of architectural history. Whereas data fusion combines multiple data forms textual descriptions, architectural drawings, and photographic evidence into a unified dataset, hierarchical analysis efficiently breaks down complex data into manageable layers, allowing the neural network to concentrate on particular features at successive levels. This all-encompassing method not only uses the RSO technique to improve the neural network's parameters, increasing model accuracy and efficiency, but it also establishes a precedent for using cutting-edge computational techniques in the conservation of cultural assets. The results of this study highlight the important advanced modeling tools like ANN-RSO are for supporting preservationists and architectural historians. This represents a major advancement in the preservation and comprehension of our architectural past, as these techniques provide improved insights into historical contexts and facilitate more realistic reconstructions of ancient buildings.

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