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# Exploration of Natural Element Form Optimization Algorithm using Spatial-Temporal Multi-Scale Alignment Graph Neural Network in Architectural Design Based on Morphological Theory

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***Abstract: -*** The construction industry has experienced important changes in recent years due to advancements in digital, artificial intelligence, and construction technologies, as well as the sector's on-going development and the advancement of science and technology. The creative growth of building industry, creative creation of architectural forms are partially supported technically by sophisticated parametric design apparatuses, the potent computing benefits of computer technology. In this manuscript, Exploration of Natural Element Form Optimization Algorithm using Spatial-Temporal Multi-Scale Alignment Graph Neural Network in Architectural Design Based on Morphological Theory (ENEF-OA-ADMT) is proposed. The STMSA-GNN and the Chaotic Coyote Algorithm (CCA) are two tools used by the proposed ENEF-OA-ADMT approach to improve architectural design based on morphological theory. The ST-MSA GNN's ability to capture intricate interactions and dependencies between several components in both space and time allows it to perform a comprehensive study of the morphological aspects of architectural designs. This graph neural network's integration of spatial and temporal dimensions enables a deeper understanding of how the architectural structural form design changes over time. The CCA optimized the ST-MSA-GNN to enhance the architectural structural form design. The proposed ENEF-OA-ADMT methodology skill fully combines these methodologies, creating a strong framework that allows architects and designers to work together to explore, refine, and create architectural structural design forms. The framework provided serves as a spur for further research, encouraging a more complete integration of technology and environment in the architectural domain. The effectiveness of proposed method is executed in python, evaluated through performance metrics encompassing accuracy, precision, specificity, Recall, computational time, F1 score, population diversification, randomness. Proposed ENEF-OA-ADMT method 34.56%, 28.63% and 21.89% higher accuracy, 34.97%, 32.13% and 21.89% higher precision and 34.68%, 20.84% and 29.76% higher randomness when compared with the existing methods such as Study of Morphological Design of Architecture from Geometric Logic Perspective (SOT-MDA-GLP), learning deep morphological networks by neural architecture search (LD-MN-NAS) and identifying degrees of deprivation from space utilizing deep learning with morphological spatial analysis of deprived urban areas (IDDS-DLMSA-DUA) respectively.

***Keywords:*** Architectural Design, Chaotic Coyote Algorithm, Exploration of Optimization, Morphological Theory, Natural Form Element, STMSA-GNN.

## I. INTRODUCTION

Architectural design is undergoing a significant metamorphosis in the modern construction industry, which is characterized by quick advances in digital technology, artificial intelligence, and creative building techniques. The convergence of advanced parametric design tools with the computational capabilities of contemporary computers has spurred a renewed interest in architectural innovation [1-3]. Architects are empowered by this revolutionary synergy to surpass traditional forms, enhancing the spirit and breadth of architectural design [4-6]. The democratization of the construction of complex buildings has been facilitated by the introduction of geometric logic principles and the development of parametric design tools. A paradigm change in the design of architectural forms may be seen in the once avant-garde, now conventional [7-9]. This progression aligns with the growing focus of the architectural community on design standards, which highlight the necessity of rational architectural forms and enhanced usefulness. Within this dynamic environment, the study adopts a dual focus, examining the interface between basic natural principles and state-of-the-art computers [10-12]. Based on fundamental ideas of Morphological Theory, takes readers on an engrossing journey into the field of natural element form optimization while the architectural world struggles with these changing dynamics [13-15]. Architects and designers are constantly aware of how reality is changing, thus they actively look for new approaches to challenge established ideas. The incorporation of cutting-edge optimization algorithms, which are inspired by the natural intelligence of the world, emphasizes this quest [16-18]. This combination has enormous disruptive potential and might lead to a new direction in architectural design. This inquiry, positioned at the confluence of theory and algorithm, tries to untangle the deep relationships between advanced algorithms and Morphological Theory [19, 20]. The voyage is expected to provide both visually striking architectural forms and optimally functional solutions. This complex confluence becomes a focus point for further research on the topic, demonstrating how innovation, technology, and nature can work together to transform the very core of architectural design.

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The problem statement for this research lays in the dynamic development of architectural design, spurred by significant breakthroughs in digital technology and new building processes. As architects adopt advanced parametric design tools, a fundamental problem develops in managing this transformational convergence. There is pressure on the architectural community to meet greater design standards by emphasizing better functionality and logical forms. This calls for investigating methods that combine natural laws with state-of-the-art computation. This work, which is based on morphological theory, aims to explore the relationships between sophisticated algorithms and architectural design, emphasizing both practicality and beauty. The fundamental issue is how to rethink the fundamentals of architectural design by utilizing the disruptive potential of combining natural element form optimization with cutting-edge algorithms.

Major contribution of this paper a follows;

- Exploration of Natural Element Form Optimization Algorithm using STMSA-GNN in Architectural Design Based on Morphological Theory (ENEF-OA-ADMT) is proposed.
- The proposed ENEF-OA-ADMT technique for architectural structural form design makes use of the ST-MSA-GNN.
- Using the Chaotic Coyote Algorithm (CCA), the proposed ENEF-OA-ADMT technique optimizes the ST-MSA-GNN to improve the architectural structural form design, which is based on morphological theory.

Remaining portion of this work structured below: section 2: literature review, section 3: describes proposed methodology' section 4: illustrates outcomes with discussion, section 5: conclusion.

## II. LITERATURE REVIEW

Zhao and Yang, [21] have presented, study of MDA from GLP. This work proposes a research methodology for geometric logic perspective-based architectural form design in order to tackle intricate structural problems. Taking structures as a case study and combining architectural form design requirements, the ideal architectural structure is examined using evolutionary algorithms. Emphasizing the validation of building plane, space optimization based displacement restrictions, geometric logic design technique includes the full design process, including building usage, site, system, production constraints. Architectural idea schemes were developed by logic construction and computer language simulation, resulting in promotion of extremely accurate building goods.

Hu et al. [22] have suggested, LD-MN with NAS. This research explores the incorporation of morphological operators into a comprehensive end-to-end deep learning system. Deep Neural Networks (DNNs) were tuned to capture realistic representations for specific tasks, whereas morphological operators give topological descriptors communicating vital information about object forms in pictures. The suggested method integrates morphological operators into DNNs with ease by using meta-learning. The gained architecture highlights how these unique morphological procedures dramatically boost DNN performance across many applications, comprising picture classification, edge discovery, semantic segmentation.

Abascal et al., [23] have presented, IDDS utilizing DLMSA of deprived urban areas. Here, addresses the information gap regarding urban deprivation in disadvantaged urban areas (DUAs) of low- and middle-income nations. This presented method determines deprivation levels resulting from rapid unplanned expansion using morphological analysis and deep learning. By using a community-based participatory approach, establishes a building footprint reference dataset. Here, modifies DL method depend on U-Net for purpose of semantic segmentation of World View 3 satellite data. Deprivation levels may be determined with the help of morphological parameters from expected structures, such as size, directionality, interior irregularity, and closeness. It contributes to creating up-to-date and disaggregated morphological spatial data for DUAs, vital for designing targeted interventions based on a detailed knowledge of physical features of deprivation.

Sun et al. [24] have presented understanding building energy efficacy by administrative with developing urban big data by DL in Glasgow. This research presented multi-source data fusion system for building energy efficacy estimation based on deep learning. Conventional parameters from Glasgow, UK's 160,000 properties' Energy Performance Certificates (EPC) and Google Street View (GSV) photos of building façades were taken into account. Performance gains were compared amongst image-only models, conventional morphological features, and the data-fusion framework. It draws attention to the possibility of using data from several sources to estimate building energy efficiency accurately and effectively. It provide city-level insights that are crucial for meeting the net-zero goals by 2050.

Salvati et al. [25] have presented defect-depend physics-informed ML framework for fatigue finite life prediction in additive manufacturing. Here, presents unique method for forecasting fatigue limited life of additively manufactured faulty materials. The solution overcomes the limits of data-hungry machine learning systems by including fracture mechanics restrictions during the training process, all while leveraging a Physics-Informed Neural Network structure. The prediction tool shows improved accuracy in taking into account morphological characteristics of faults by using extensive defect analysis from literature, including computer tomography and fractography, together with experimental findings. This development might lead to previously unheard-of levels of precision in novel structural design techniques that respect the principles of fracture mechanics and only require a smaller experimental dataset.

Wu et al. [26] have suggested, cultivating historical heritage region vitality utilizing urban morphology method depend on big data with ML. Here, examines the consistency or divergence of urban morphological components affects the vitality of historic and urban regions using multi-source large geospatial data, utilizing ridge regression and Light GBM. Our analysis of twelve Chinese towns reveals that the factors that affect historic areas aren't the same as those that affect urban vitality. These characteristics also show change between cities and during the day. Using measurements of urban form, vitality generated from massive geospatial data, the study presents a quantitative, reproducible framework for heritage adaptation. This theoretical support for historical protection, urban expansion, and economic growth helps to explain the shapes of heritage areas.

Seydi et al. [27] have suggested quadratic morphological DNN fusing radar with optical data for mapping of burned regions. Here, presents a unique methodology for mapping burnt regions by combining post-event sentinel-2 data by multi-temporal sentinel-1 coherence images. QMDNN-Net was a proposed deep feature extraction architecture that combines a set of hybrid QM techniques with convolution layers. QMDNN-Net functions as a deep Siamese network and consists of two streams for deep feature extraction from sentinel-2 images with multi-temporal coherence data. Both streams have an identical structure with similar number of group-dilated convolution blocks, QM layers. QMDNN-Net defines quadratic dilation, erosion, its output was average of such processes. Sentinel-1, sentinel-2 imagery-based real-world wildfire dataset were used to assess efficacy of QMDNN-Net-based wildfire mapping.

## III. PROPOSED METHODOLOGY

In this section, Exploration of Natural Element Form Optimization Algorithm using STMSA-GNN in Architectural Design Based on Morphological Theory is discussed. In the proposed methodology section dataset, neural network and optimization are described. Block diagram of proposed ENEF-OA-ADMT is given below in Figure 1,

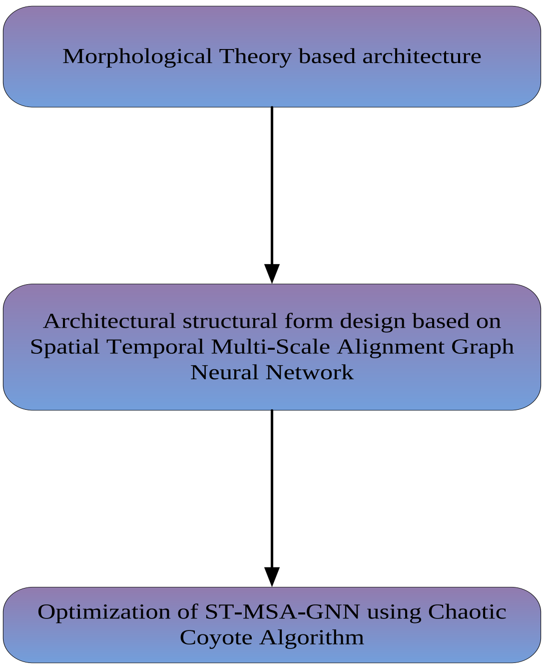


**Figure 1:** Block diagram of ENEF-OA-ADMT

*A. Architectural structural form design based on Spatial Temporal Multi-Scale Alignment Graph Neural Network*

This section discusses the ST-MSA-GNN [28]. An essential component of the ENEF-OA-ADMT system is the ST-MSA-GNN. This neural network is intended to process data at many dimensions, both spatial and temporal, in the context of architectural design. The ST-MSA GNN is able to do a thorough analysis of the morphological features of architectural designs because it is skilled at capturing complex interactions and dependencies between numerous components in both space and time. It attains novel idea for scientific structural design. Architectural designs change progressively throughout time, with elements from one stage influencing other stages. Recurring patterns are widespread and represent popular design concepts. Precise forecasting of the evolution of architectural forms improves comprehension and facilitates morphological study. To enable a coherent analysis of the morphological evolution of architectural design, the investigation utilizes uniform network architecture in three compositions. Transportation network representations with node signal properties are made possible by using spectrogram theory, which extends 2D convolution to graph topologies. However, samples containing graphs have higher computational complexity, mostly because of the composition of Laplace matrix U features. It is expensive to directly decompose Laplace matrix eigenvalues in large-scale networks. This paper addresses the problem with an effective solution based on Chebyshev polynomials it is shown in equation (1),

$$i_\theta * Iz = i\theta(N)z = \sum_{m=0}^{M-1} \theta_m V_m(\tilde{N})z \tag{1}$$

Here, $i\theta$ represent the eigenvalues of Laplace matrix, $z$ represent the traffic flow signal, $N$ represent the Laplace matrix, $M$ represent the end node and $V_m$ represent the traffic signal time at end node. A CNN directly working on graph, coupled with local first-order approximation of spectrogram convolution, boosts efficacy of the convolution structure it is shown in equation (2),

$$J^{(n)} = \mathrm{Re}\,LU\left(\hat{C}J^{(n-1)}Y^{(1-1)}\right) \tag{2}$$

Here, $J^{(n)}$ represent the convolution output, $\hat{C}$ represent the adjacent matrix and $\mathrm{Re}LU$ denotes the activation function. Adjacent time slices of a node's signal are updated merging through typical convolution layer in time dimension after node nearby information is captured spatially using a graph convolution operation. The first time dimension level operation is therefore stated as in equation (3),

$$Z_j^{(m)} = \mathrm{Re}LU\left(\phi * \left(\mathrm{Re}LU\left(i\theta *_I \hat{Z}_j^{(n-1)}\right)\right)\right) \in R^{E_t \times P \times V_t} \tag{3}$$

Here, $Z_j^{(m)}$ short cycle dependence, $\mathrm{Re}LU$ denotes the activation function, $*$ means standard convolution operation and $\phi$ represent temporal dimension convolution kernel. In order to preserve similarity when propagating graph neural networks, pairwise relations must be captured, a concept taken from CRF. Depend on such facts, CRF is shown in equation (4),

$$R\left(J^{(n)} \mid Q^{(n)}\right) = \frac{1}{B\left(Q^{(n)}\right)} \exp\left(-G\left(J^{(n)} \mid Q^{(n)}\right)\right) \tag{4}$$

Here, $J^{(n)}$ represent the convolution output; $Q^{(n)}$ represent the random variable under in condition, $B$ represent the normalize factor and $G$ denotes the energy function. Learn different similarity from hidden layer, pairwise energy function expressed in equation (5),

$$\phi_r\left(J_k^{(n)}, J_l^{(n)}, Q_k^{(n)}, Q_l^{(n)}\right) = i_{kl}\left\|J_k^{(n)} - J_l^{(n)}\right\|_2^2 \tag{5}$$

Here, $\phi_r$ represent temporal dimension convolution kernel, $J^{(n)}$ represent convolution output, $Q^{(n)}$ represent the random variable under in condition and $i_{kl}$ denotes the similarity of nodes $k$ and $l$. The distance between nodes will enlarged, consequently, same nodes mapped to parallel position in hidden space. Energy shown in equation (6),

$$G\left(J_k^{(n)} \mid Q_l^{(n)}\right) = \alpha\left\|J_k^{(n)} - Q_k^{(n)}\right\|_2^2 + \beta \sum_{l \in P_k} i_{kl}\left\|J_k^{(n)} - J_k^{(n)}\right\|_2^2 \tag{6}$$

Here, $G$ denotes the energy function, $i_{kl}$ denotes the similarity of nodes $k$ and $l$ , $J^{(n)}$ represent the convolution output, $Q^{(n)}$ represent the random variable under in condition and $\alpha, \beta$ denotes the non-negative parameters. To allow CRF to aid comfort similarity restrain in a graph convolution, an objective function is shown in equation (7),

$$M_{CRF} = \sum_{m=1}^{N-1} \frac{\gamma}{2} \left\| J^{(n)} - H_n\left(\hat{C} J^{(n-1)}, Y(n)\right) \right\|_H^2 \tag{7}$$

Here, $J^{(n)}$ represent the convolution output, $\hat{C}$ represent the adjacent matrix, $N$ denotes number of layers of graph convolution network, $M$ denotes objective function. The moderate conditions, it becomes harder to require the similarity constraint to be satisfied as $\gamma$ grows. The goal is to use the objection function displayed in and regularization to the convolution output in order to resolve this problem is shown in equation (8),

$$M_{CRF} = \sum_{n=1}^{N-1} \frac{\gamma}{2} \left| J^{(n)} - H_n\left(\hat{C}, J^{(n-1)}, Y^{(n)}\right) \right|_H^2 + T\left(J^{(n)}\right) \tag{8}$$

Here, $J^{(n)}$ represent the convolution output, $M$ denotes the objective function, $\hat{C}$ represent the adjacent matrix, $M$ denote the objective function, $N$ denotes number of layers of graph convolution network, $T$ denotes regularization function to compute the back propagation. To obtain time shift, extract weight representation, this approach now chooses the attention mechanism. Regarding the chosen time frame, the overall weight represented by equation (9),

$$z_{k,v}^{r} = \sum_{s \in S} \alpha_{k,v}^{r,s} z_{k,v}^{r,s} \tag{9}$$

Here, $s$ represent the total weight, $r$ time interval in days, $S$ represent the time interval and $z_{k,v}^{r,s}$ represent the hidden state. It may derive the weight formally by comparing the prior hidden state by temporal, spatial representations gained short-term memory. Each $r$ from the day before is used to obtain the cycle representation. The representation of time given in equation (10),

$$\hat{Z}_{k,v}^{r} = \mathrm{Re}\, LU\left(Z_{k,v}^{r}, \hat{Z}_{k,v}^{r-1}\right) \tag{10}$$

Here, $\mathrm{Re}LU$ denotes the activation function and $Z_{k,v}^{r}$ denotes the weight. The daily and weekly component production in multi-scale fusion could be more challenging and crucial. Nevertheless, daily and weekly cycle components might not be useful in predicting outcomes on other days when there are no nitid traffic cycle patterns. As a result, each node's output weight changes when the three components are fused, and it must learn from past experience. In conclusion, following fusion, the ultimate predicted result is shown in equation (11),

$$\hat{A} = Y_j \Theta \hat{A}_j + Y_f \Theta \hat{A}_f + Y_y \Theta \hat{A}_y \tag{11}$$

Here, $\Theta$ denotes inner product and $Y_j, Y_f$ *and* $Y_y$ are represent the learning parameters. The forecasting aim is influenced to varying degrees by the temporal-dimensional components, as shown by the inner products and learning parameters. The combination of spatial and temporal dimensions in this graph neural network allows for a more thorough comprehension of the changing architectural structural design throughout time.

*B. Optimization of ST-MSA-GNN using Chaotic Coyote Algorithm*

In this section, Chaotic Coyote Algorithm (CCA) [29] is discussed. The optimization method might incorporate CCA, which is recognized for its dynamic and chaotic nature. This might entail adding unpredictability or disorder to some areas of the design investigation in order to increase the diversity of possible solutions. The morphological theory-based ENEF-OA-ADMT offers a basis, the spatial-temporal relationship-capturing ST-MSA-GNN supports decision-making, and the chaotic dynamics-introducing CCA improves the optimization process. It's crucial to remember that the efficiency of this kind of method would rely on the particulars of the algorithms, how they are parameterized, and how effectively they work in tandem to accomplish the objectives of architectural design optimization.

***Step 1:*** Initialization

The Chaotic Coyote Algorithm (CCA) takes a different approach from traditional algorithms by separating its population into discrete packs, each with custom social influences. Because it only requires a few critical hyper parameters, comprising number of packs, population size, maximum number of generations, technique is known for its simplicity. The individual coyotes that make up each pack are initiated inside the search space delineated by predetermined intervals. It is shown in equation (12),

$$so_{e,l}^{r,v} = nd_l + t_l \cdot \left(wd_l - nd_l\right) \tag{12}$$

Here, $e$ represent the coyotes, $r$ represent the packs, $wd_l$ and $nd_l$ are represented the interval $t_l$ represent the random number inside $[0,1]$ made by uniform probability distribution and $v$ denotes iteration. The alpha coyote in the wild is the one with the finest social structure. It denotes best objective function cost in CCA and is represented by equation (13),

$$alpha^{r,v} = \left\{so_e^{r,v} \mid \arg_{e=\{1,2,\ldots,P^e\}} \min_{h\left(so_e^{r,v}\right)}\right\} \tag{13}$$

Here, $e$ represent the coyotes, $r$ represent the packs and $v$ denotes the iteration

***Step 2:*** Random generation

After initialization, weight parameters are formed randomly generated. The values generated randomly between $0$ and $1$.

***Step 3:*** Fitness function

It makes random solution form initialized values. It intended utilizing optimizing parameter. Thus it is shown in equation (14),

$$Fitness\ Function = optimizing\left[Z_{k,v}^{r}\, and\ Q_l^{(n)}\right] \tag{14}$$

***Step 4:*** Exploration Phase

Updates to the social state are produced during the CCA exploration phase in response to the alpha coyote and the social tendency. Equation (15) indicates that the cause of these effects is two randomly selected coyotes within the pack.

$$new\_so_e^{r,v} = so_e^{r,v} + t_1 \cdot \delta_v + t_2 \cdot \delta_c \tag{15}$$

Here, $e$ represent the coyotes, $r$ represent the packs, $v$ denotes the iteration, $t_1$ and $t_2$ represent weights of pack with alpha influence, $\delta_c$ denotes alpha coyote, $\delta_v$ denotes the social tendency. To go on to following iteration, coyotes select social state that best fits surrounding conditions. As Equation (16) illustrates, this translates to selecting the social condition with best objective function cost.

$$so_e^{r,v+1} = \begin{cases} new\_so_e^{r,v}, & fnew\_fit < fit_e^{r,v} \\ so_e^{r,v}, & otherwise \end{cases} \tag{16}$$

Here, $e$ represent the coyotes, $r$ represent the packs and $v$ denotes the iteration.

***Step 5:*** Exploitation Phase

In exploitation phase of CCA, a puppy with age 0 is produced, using both scatter and association probability, shown in equation (17),

$$pu_l^{r,v} = \begin{cases} so_{m_1 \cdot l}^{r,v}, if\ rand_l < R_c\ or\ l = l_1 \\ so_{m_2 \cdot l}^{r,v}, if\ rand_l \geq R_u + R_c\ or\ l = l_2 \\ T_l, otherwise \end{cases} \tag{17}$$

Here, $r$ represent the packs and $v$ denotes the iteration, $m_1$ and $m_2$ are represented the selected coyotes from the pack, $l_1$ and $l_2$ are represented the random dimension of the problem, $T_l$ represent the random number inside decision bound of dimension, $rand_l$ denotes the random number inside $[0,1]$. Every repetition, the coyote's age is updated, yielding the following equation (18),

$$age_e^{r,v+1} = age_e^{r,v+1} + 1 \tag{18}$$

Here, $e$ represent the coyotes, $r$ represent the packs and $v$ denotes the iteration. The optimization problem is solved by choosing the coyote that is most adaptable out of all the packs.

***Step 6:*** Termination

In the STMSA-GNN, weight parameters for generators are optimized using the CCA, dynamically adjusting weights inspired by celestial mechanics. The iterative refinement, guided by halting criteria $so_{e,l}^{r,v} = so_{e,l}^{r,v} + 1$, ensures optimal weight convergence, maximizing STMSA-GNN's generator performance. Then Flowchart of CCA for optimizing the weight parameter of STMSA-GNN for enhances the architectural structural form design based on morphological theory is given below in Figure 2,

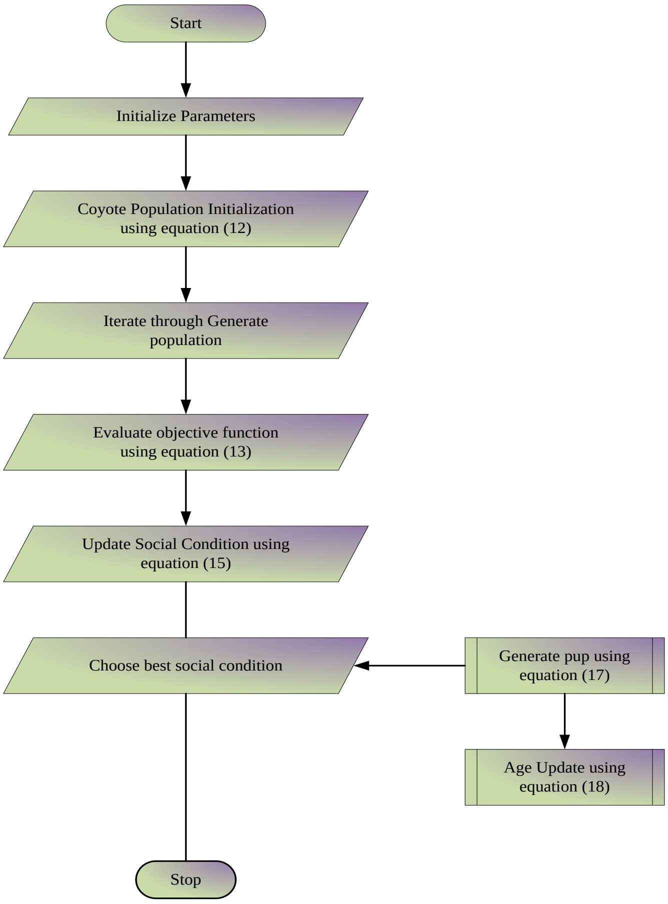


**Figure 2:** Flowchart of CCA for optimizing the weight parameter of STMSA-GNN for enhances the architectural structural form design based on morphological theory

*C. Architectural form design under Geometric logic*

*1) Factors Influencing Formation of Complex Architectural Structure Form.*

Sometimes, to attain different goals, building's structure form system divided into two corners, structure itself divided into different function schemes. These complex form buildings have internal structures that are separated from external forms, but this does not mean that the structure deviates from the logic of building form generation. Even with intricate architectural designs, some buildings nonetheless follow the conventional floor plan separation of rooms for interior functions. In this instance, the building's structural system can be split into many sections based on the real demand, with the form creation logic obtaining the structural section most closely associated with the shape. The more structured area of the interior can use the conventional beam, plate, column system's straightforward construction. Intended plan prevents needless financial losses brought on by the difficulty of straightforward issues. For instance, the central square core tube of super higher-rise China Respect Project is simple component of entire structural scheme, but structure's perimeter, which includes giant column, waist truss systems that alter as the building's form changes, is more complex.

*2) Structural Mechanical Factor*

Since a structure's mechanical qualities directly affect its applicability, longevity, and safety, mechanical considerations take precedence when designing structures. In general, special mechanical properties are needed by complicated building structural systems in order to realize complex shapes. It is capable of efficiently distributing its load, stress across entire structural system. It ability to distribute load uniformly suggests its great efficiency, as per the principles of structural mechanics. Because of this, complex structural system itself has a relatively higher mechanical rationality, makes it more logical to create than conventional beam, plate, column system. Structural optimization and form-based optimization are the two main subfields of optimization. Form-based optimization involves using form as optimization variable, selecting best optimization process, obtaining optimal form. This process referred to arithmetical technique of making form because it requires high level of structural engineering expertise. However, when building surface form established under impact of structural indicators, structural component system is analyzed and optimized using the structural design software PKPM and the finite element program ANSYS. The study's primary focus is on static, modal, and buckling analysis. To find the best solution for the structure's mechanical characteristics, secondary components are tested and examined.

*3) Structural with Functional Factor*

In definite cases, construction of structural system offer a related dynamic system for configuration space features of crowd movement trend function; for instance, structure's linear setup can identify the crowd flow line's single path. Certain behavioural patterns or spatial uses may be enabled by the structure's set size and transparency of the area. The conventional structure also reflects this association, which is not exclusive to complex structure; nonetheless, complex structure may be inferred from the more comprehensively obvious. Particularly after using parameterized technology, feature space behavior integration, and intellectual programming language through process, the system's structure becomes further varied, pertinent, and useful. The direct integration of structure and function also reflects the impact of function on the former. The distinction among structural skin, space has gotten progressively hazy as architecture has developed in a more diverse manner. Occasionally, the structure serves as a functional space, and the structure also reflects the space. With its beamless floor, seaweed light columns reflecting building, the Toyo ITO Sendai Media Center, for instance, has a totally free system of behavior, no room separation. These structural hollow columns have higher degree of structure-function integration because of their creative design, which includes uses for them as stairwells, elevators, equipment, pipelines, and little rest areas.

*D. Geometric logic in architectural structural form design*

*1) Selective Construction Starting Point*

The nonlinear thinking technique, supports flexibility, uncertainty in the design process, resists stylization and solidification of thought processes, serves as the foundation for the building of parametric geometric logic. Parametric geometric logic building, thus, encourages constructors to approach task of geometric logic creation from several angles. They can get a deeper grasp of the design environment during the design process by updating and reconstructing, and they can eventually achieve a state of balance with the limits of the design. Architectural design is complicated, nevertheless. Parameterized geometric logic building should first define design goals and conduct a detailed analysis of the interaction between different factors and the surrounding environment. As such, the construction begins with one or more discrete geometric logics, as opposed to the conventional top-down method.

*2) Select Parameters*

Improving the variable selection is a critical step in the construction of parameterized logic. The optimum control over the parameterized geometric model can only be achieved by choosing the appropriate parameters. In general, number of parameters set depend on less-is-more principle, with an emphasis on setting the parameters during the early stages of geometric logic construction to minimize parameter adjustments during the construction process. The parameters chosen to meet basic conditions of architectural form control precision. In design process, architect first analyzes the desired geometry logically, creates logical framework on computer, develops script, debugs it. When logical linkages are unclear, architects most frequently utilize debugging, which is a crucial component of programming. In addition to confirming that the software operates correctly, debugging may help the constructor solve errors by offering guidance and motivation. The feedback mechanism is dynamic. Furthermore, the geometric shape of an architectural form typically possesses internal principles and a somewhat stable topological structure. To complete parametric building tasks, architects depend on well-established processes. For example, they can produce hyperboloid minimum surfaces directly by utilizing MATLAB and Mathematical functions.

*3) Output*

In theory, the creation of a parametric model completes the process of parametric geometric logic construction. However, in actual practice, architects need a solid model to be output for further tasks like rendering, animation, and 3D printing. In order to facilitate the building and implementation of projects, parameterized software must simultaneously send the manufacturer the building model and the management database containing all production components, such as material attributes, positioning parameters, and naming guidelines. As well as being the final stage in constructing parametric geometric logic, the output of the result is also the crucial component that moves the logic's development from thinking awareness to material form. Currently, different digital manufacturing software and parametric software have different file output formats. File format conversion between different software programs is a common task for architects. While file formats with limited storage capacity are generally well-compatible, information loss is a common occurrence and model accuracy is insufficient. High precision file formats are ideal for storing different parameter model data, but they take up a lot of room and operate slowly. Thus, at the outset of geometric logic creation, architects must take the output of outcomes into account. These days, 3DS, IGCS, OBJ, and other output formats are often employed.

## IV. RESULT AND DISCUSSION

In this paper, Exploration of Natural Element Form Optimization Algorithm using STMSA-GNN in Architectural Design Based on Morphological Theory is discussed. The proposed technique is implemented in python and evaluated by using several performance metrics like accuracy, precision, specificity, Recall, computational time, F1 score, population diversification, randomness. The result of ENEF-OA-ADMT approaches was compared with existing SOT-MDA-GLP, LD-MN-NAS and IDDS-DLMSA-DUA techniques.

### *A. Performance measures*

This is a crucial step for determining the exploration of optimization algorithm. Performance measures to evaluate to access performance such as accuracy, precision, specificity, Recall, computational time, F1 score, population diversification, randomness.

*1) Accuracy*

The value of accuracy is deliberate as ratio of number of samples precisely characterized by system by total samples. It is computed using equation (19),

$$accuracy = \frac{TP + TN}{TP + TN + FN + FP} \tag{19}$$

Here, $TP$ signifies true positive, $TN$ denotes true negative, $FN$ indicates false negative, $FP$ signifies false positive.

*2) Precision*

Precision computes number of true positives divided through true positives plus number, false positive number and it is given by the equation (20),

$$precision = \frac{TN}{FP + TN} \tag{20}$$

Here, $TN$ represent true negative and $FP$ represent false positive.

*3) F1 score*

A popular statistic for assessing the performance of the model in binary classification issues is F1-score. The harmonic mean of recall, precision is what it is. It is shown in equation (21),

$$F1 - score = 2 \times \frac{\Pr ecision \times \operatorname{Re} call}{\Pr ecision + \operatorname{Re} call} \tag{21}$$

*4) Computational time*

It is amount of time required to complete computational process. A calculation refers sequence of rule applications, the computation time proportional to number of rule applications.

*5) Recall*

Recall is intended by dividing total number of true positive, false negative predictions by number of true positives. The model's capacity to collect all pertinent instances is measured. It is shown in equation (22),

$$\operatorname{Re} call = \frac{TP}{TP + FN} \tag{22}$$

Here, $TP$ represent true positive, $FN$ denotes false negative.

*6) Specificity*

Specificity estimates proportions of negative, given in equation (23),

$$specificity = \frac{TP}{TN + FN} \tag{23}$$

Here, $TP$ represent true positive, $TN$ denotes true negative and $FN$ indicates false negative.

*7) Population diversification*

Population diversification in optimization algorithms seeks to explore a wide range of locations in the search space to increase the likelihood of discovering optimum or innovative solutions. Stronger exploration is often associated with higher population diversity.

*8) Randomness*

Randomness in the context of algorithms and formulae usually means adding unpredictability or variability. This may be accomplished by adding aspects of chance or indeterminacy using a random number generator. It is shown in equation (24),

$$Randomness = V + F \times N \tag{24}$$

Here, $V$ denotes the base value, $F$ denotes the random factor and $N$ denotes the random number.

*B. Performance analysis*

Figure 3 to 10 depicts the simulation results of proposed ENEF-OA-ADMT method proposed. Proposed ENEF-OA-ADMT method is analysed with existing techniques SOT-MDA-GLP, LD-MN-NAS and IDDS-DLMSA-DUA.

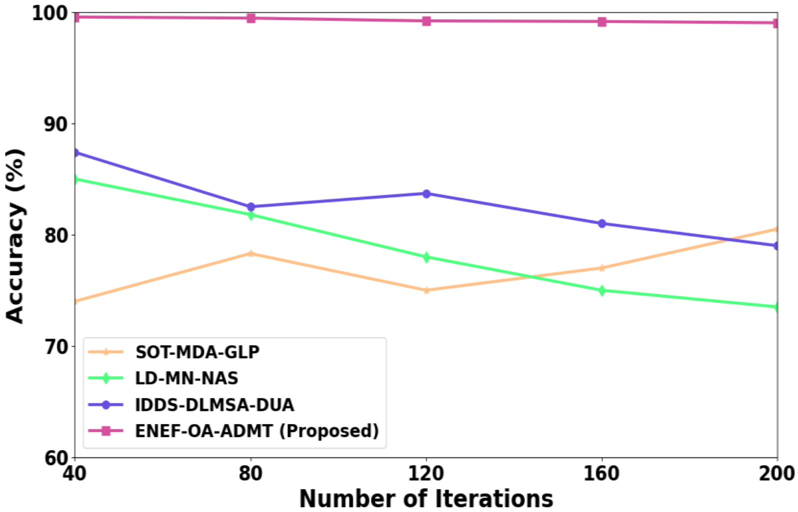


**Figure 3:** Accuracy analysis

Figure 3 depicts accuracy analysis. Here, ENEF-OA-ADMT technique attains 34.56%, 28.63% and 21.89% higher accuracy for enhances the architectural structural form design; as analysed with existing SOT-MDA-GLP, LD-MN-NAS and IDDS-DLMSA-DUA methods respectively.

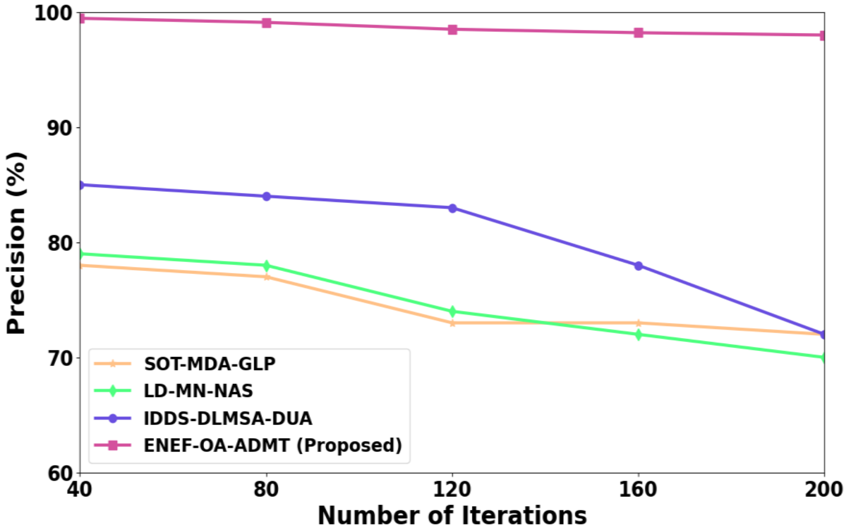


**Figure 4:** Precision analysis

Figure 4 depicts precision analysis. Here, ENEF-OA-ADMT technique attains 34.97%, 32.13% and 21.89% higher precision for enhances the architectural structural form design; as analysed with existing techniques likes SOT-MDA-GLP, LD-MN-NAS and IDDS-DLMSA-DUA.

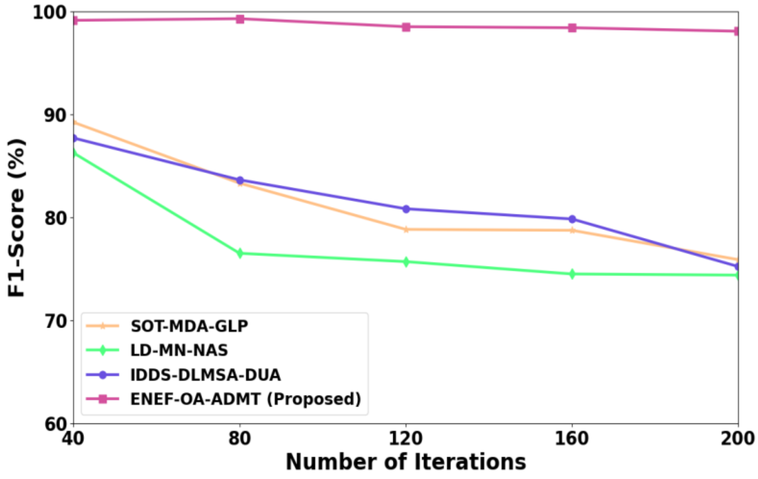


**Figure 5:** F1-score analysis

Figure 5 depicts F1-score analysis. Here, proposed ENEF-OA-ADMT technique attains 19.45%, 30.72% and 23.72% higher F1-score for enhances the architectural structural form design; as analysed with existing techniques likes SOT-MDA-GLP, LD-MN-NAS and IDDS-DLMSA-DUA.

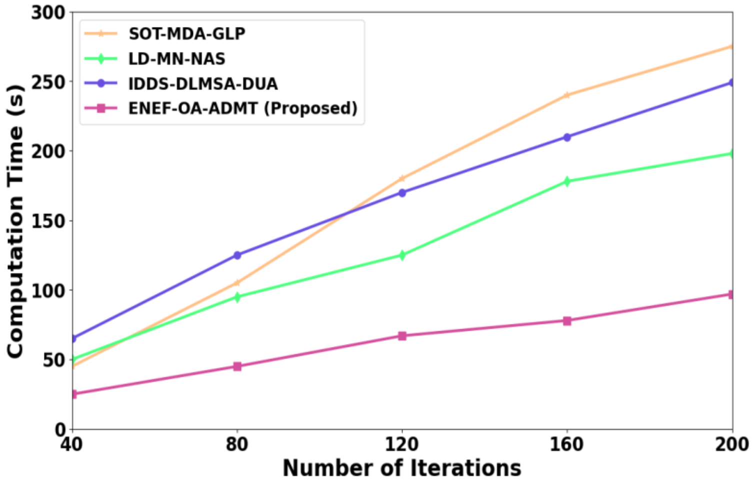


**Figure 6:** Computation time analysis

Figure 6 depicts computational time analysis. Here, ENEF-OA-ADMT technique attains 33.93%, 22.54% and 27.19% lower computational time for enhances the architectural structural form design; as analysed with existing techniques likes SOT-MDA-GLP, LD-MN-NAS and IDDS-DLMSA-DUA.

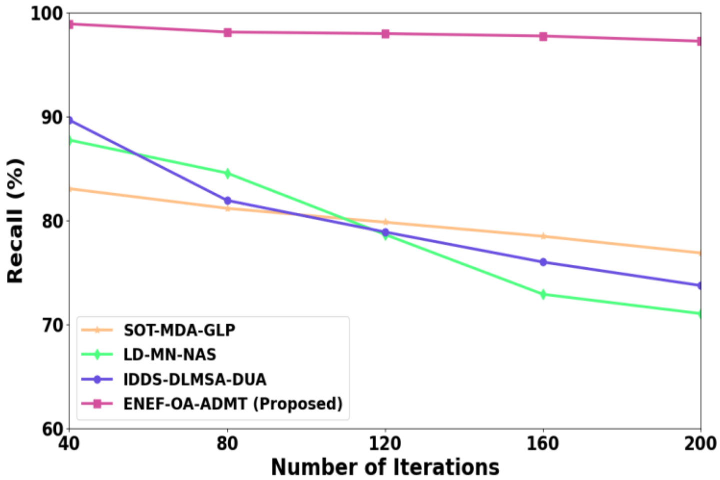


**Figure 7:** Recall analysis

Figure 7 depicts recall analysis. Here, ENEF-OA-ADMT technique attains 34.75%, 25.41% and 17.63% higher recall for enhances the architectural structural form design; as analysed with existing techniques likes SOT-MDA-GLP, LD-MN-NAS and IDDS-DLMSA-DUA.

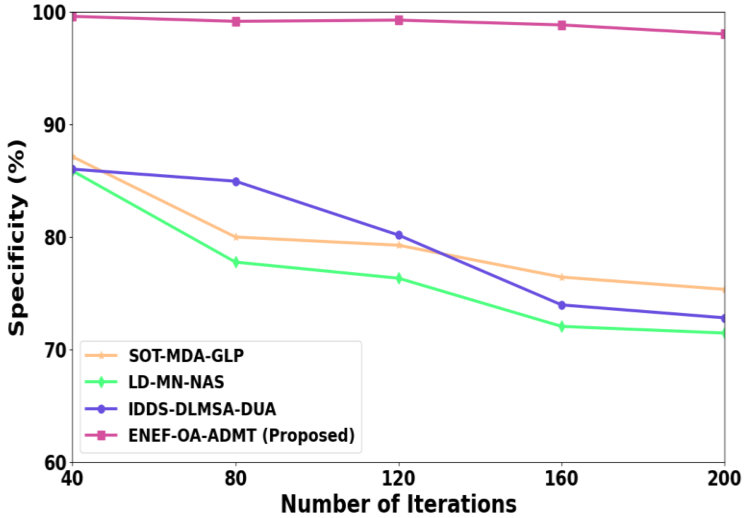


**Figure 8:** Specificity analysis

Figure 8 depicts specificity analysis. Here, ENEF-OA-ADMT technique attains 21.82%, 31.91% and 16.78% higher specificity for enhances the architectural structural form design; as analysed with existing techniques likes SOT-MDA-GLP, LD-MN-NAS and IDDS-DLMSA-DUA.

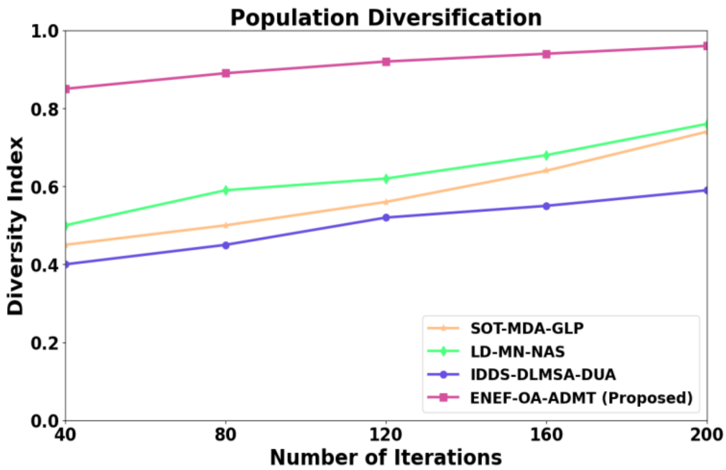


**Figure 9:** Population diversification analysis

Figure 9 depicts population diversification analysis. Here, ENEF-OA-ADMT technique attains 23.55%, 15.97% and 33.69% higher population diversification for enhances the architectural structural form design; as compared to the existing SOT-MDA-GLP, LD-MN-NAS and IDDS-DLMSA-DUA methods respectively.

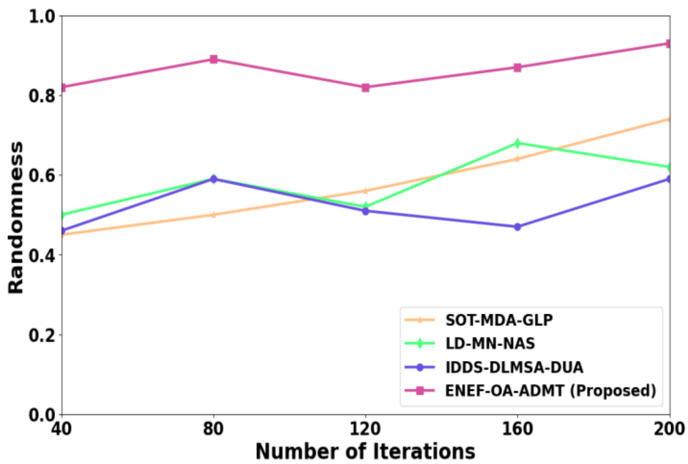

**Figure 10:** Randomness analysis

Figure 10 depicts randomness analysis. Here, ENEF-OA-ADMT technique attains 34.68%, 20.84% and 29.76% higher randomness for enhances the architecture structural form design; as analysed with existing techniques likes SOT-MDA-GLP, LD-MN-NAS and IDDS-DLMSA-DUA.

*C. Discussion*

The Exploration of Natural Element Form Optimization Algorithm using STMSA-GNN in Architectural Design Based on Morphological Theory technique is proposed. The proposed ENEF-OA-ADMT technique introduces an architectural design based exploration of optimization algorithm of Natural form element. This proposed method using the ST-MSA-GNN for architectural structural form design and Chaotic Coyote Algorithm (CCA) for optimizing the ST-MSA-GNN. The efficient use of this novel methodology will rely on the particular features of the algorithms, how they are parameterized, and how effectively they work in tandem to accomplish the objectives of architectural design optimization. The proposed ENEF-OA-ADMT approach is compared to the existing SOT-MDA-GLP, LD-MN-NAS and IDDS-DLMSA-DUA techniques. According to the finding analysis the proposed system method outperformed the others. In terms of results, the approach's average highest outcomes were compared to the average highest outcomes of existing techniques such as SOT-MDA-GLP, LD-MN-NAS and IDDS-DLMSA-DUA. The accuracy values of SOT-MDA-GLP, LD-MN-NAS and IDDS-DLMSA-DUA are lower than proposed method. The proposed framework achieves an average accuracy of 99.93% compared to 92.62% for the comparison approaches. Similar to this, the precision of proposed method is 98.67% analyzed with average precision of comparison techniques of 94.12%. The proposed method ENEF-OA-ADMT has high accuracy and precision evaluation metrics than existing methods. Therefore, comparative methods are expensive than the proposed technique. As a result, the proposed technique improves enhances the architectural design based exploration of optimization algorithm of Natural form element.

## V. CONCLUSION

In this section, Exploration of Natural Element Form Optimization Algorithm using Spatial-Temporal Multi-Scale Alignment Graph Neural Network in Architectural Design Based on Morphological Theory was successfully implemented. This proposed method using Spatial-Temporal Multi-Scale Alignment Graph Neural Network and Chaotic Coyote Algorithm to represents a substantial breakthrough in architectural structural design based on morphological theory. This innovative method enhances the architectural structural form design. When compared to existing approaches such as SOT-MDA-GLP, LD-MN-NAS and IDDS-DLMSA-DUA, the proposed ENEF-OA-ADMT model outperform them. Notably, it increases specificity by 21.82%, 31.91% and 16.78%, while increasing population diversification by 23.55%, 15.97% and 33.69%. Furthermore, when compared to its equivalents, the ENEF-OA-ADMT strategy achieves a significant decrease in computing time, boasting 33.93%, 22.54% and 27.19% reduced processing times. This validates its effectiveness in enhances the architectural design based exploration of optimization algorithm of Natural form element.

## REFERENCES


[1] Sun, L., Wang, W., Zhang, C., Cheng, M., Zhou, Y., Yang, Y., &Ouyang, Z. (2022). Multiple optimization strategies for improving photocatalytic performance of the h-BN/flower-ring g-C3N4 heterostructures: Morphology engineering and internal electric field effect. *Chemical Engineering Journal*, *446*, 137027.

[2] Zhang, C., Qin, D., Zhou, Y., Qin, F., Wang, H., Wang, W., ...&Zeng, G. (2022). Dual optimization approach to Mo single atom dispersed g-C3N4 photocatalyst: morphology and defect evolution. *Applied Catalysis B: Environmental*, *303*, 120904.

[3] Li, C., Peng, Q., Qi, X., Chen, Y., Gong, X., Wang, X., ...& Du, Y. (2022). Morphology optimization strategy of flower-like CoNi2S4/Co9S8@ MoS2 core@ shell nanocomposites to achieve extraordinary microwave absorption performances. *Journal of Colloid and Interface Science*, *606*, 1128-1139.

[4] Jiang, Y., Wu, D., Cao, J., Jiang, L., Zhang, S., & Wang, D. (2023). Eyeblink detection algorithm based on joint optimization of VME and morphological feature extraction. *IEEE Sensors Journal*.

[5] Lee, D. H., Kim, D. H., Kim, T., Lee, D. C., Cho, S., & Park, T. (2022). Solid-solvent hybrid additive for the simultaneous control of the macro-and micro-morphology in non-fullerene-based organic solar cells. *Nano Energy*, *93*, 106878.

[6] Yao, R., Guo, C., Deng, W., & Zhao, H. (2022). A novel mathematical morphology spectrum entropy based on scale-adaptive techniques. *ISA transactions*, *126*, 691-702.

[7] Belachew, N., &Hinsene, H. (2022). Preparation of zeolite 4A for adsorptive removal of methylene blue: optimization, kinetics, isotherm, and mechanism study. *Silicon*, *14*(4), 1629-1641.

[8] Rahbar, M., Mahdavinejad, M., Markazi, A. H., &Bemanian, M. (2022). Architectural layout design through deep learning and agent-based modeling: A hybrid approach. *Journal of Building Engineering*, *47*, 103822.

[9] Wang, N., Wang, Y., &Er, M. J. (2022). Review on deep learning techniques for marine object recognition: Architectures and algorithms. *Control Engineering Practice*, *118*, 104458.

[10] Idrissi, M., Salami, M., &Annaz, F. (2022). A review of quadrotor unmanned aerial vehicles: applications, architectural design and control algorithms. *Journal of Intelligent & Robotic Systems*, *104*(2), 22.

[11] Lo, S. K., Liu, Y., Lu, Q., Wang, C., Xu, X., Paik, H. Y., & Zhu, L. (2022). Toward trustworthy ai: Blockchain-based architecture design for accountability and fairness of federated learning systems. *IEEE Internet of Things Journal*, *10*(4), 3276-3284.

[12] Li, Q., Zhao, X., Zhang, Z., Xun, X., Zhao, B., Xu, L., ...& Zhang, Y. (2022). Architecture design and interface engineering of self-assembly VS4/rGOheterostructures for ultrathin absorbent. *Nano-Micro Letters*, *14*(1), 67.

[13] Lo, S. K., Lu, Q., Zhu, L., Paik, H. Y., Xu, X., & Wang, C. (2022). Architectural patterns for the design of federated learning systems. *Journal of Systems and Software*, *191*, 111357.

[14] Rahbar, M., Mahdavinejad, M., Markazi, A. H., & Bemanian, M. (2022). Architectural layout design through deep learning and agent-based modeling: A hybrid approach. *Journal of Building Engineering*, *47*, 103822.

[15] Li, J., Li, D., Zheng, Y., Yao, Y., & Tang, Y. (2022). Unified modeling of regionally integrated energy system and application to optimization. *International Journal of Electrical Power & Energy Systems*, *134*, 107377.

[16] Mohanty, A., Nag, K. S., Bagal, D. K., Barua, A., Jeet, S., Mahapatra, S. S., &Cherkia, H. (2022). Parametric optimization of parameters affecting dimension precision of FDM printed part using hybrid Taguchi-MARCOS-nature inspired heuristic optimization technique. *Materials Today: Proceedings*, *50*, 893-903.

[17] Lee, Y. L., Lee, K., Ko, C. H., &Roh, H. S. (2022). Optimization of nano-catalysts for application in compact reformers. *Chemical Engineering Journal*, *431*, 134299.

[18] Mangaraj, S. R., Bagal, D. K., Parhi, N., Panda, S. N., Barua, A., &Jeet, S. (2022). Experimental study of a portable plasma arc cutting system using hybrid RSM-nature inspired optimization technique. *Materials Today: Proceedings*, *50*, 867-878.

[19] Basiony, M., Ouyang, L., Wang, D., Yu, J., Zhou, L., Zhu, M., ...& Zhang, L. (2022). Optimization of microbial cell factories for astaxanthin production: Biosynthesis and regulations, engineering strategies and fermentation optimization strategies. *Synthetic and Systems Biotechnology*, *7*(2), 689-704.

[20] Qian, T., Chen, X., Xin, Y., Tang, W., & Wang, L. (2022). Resilient decentralized optimization of chance constrained electricity-gas systems over lossy communication networks. *Energy*, *239*, 122158.

[21] Zhao, L., & Yang, Y. (2022). A Study of the Morphological Design of Architecture from a Geometric Logic Perspective. *Security and Communication Networks*, *2022*.

[22] Hu, Y., Belkhir, N., Angulo, J., Yao, A., &Franchi, G. (2022). Learning deep morphological networks with neural architecture search. *Pattern Recognition*, *131*, 108893.

[23] Abascal, A., Rodríguez-Carreño, I., Vanhuysse, S., Georganos, S., Sliuzas, R., Wolff, E., &Kuffer, M. (2022). Identifying degrees of deprivation from space using deep learning and morphological spatial analysis of deprived urban areas. *Computers, environment and urban systems*, *95*, 101820.

[24] Sun, M., Han, C., Nie, Q., Xu, J., Zhang, F., & Zhao, Q. (2022). Understanding building energy efficiency with administrative and emerging urban big data by deep learning in Glasgow. *Energy and buildings*, *273*, 112331.

[25] Salvati, E., Tognan, A., Laurenti, L., Pelegatti, M., & De Bona, F. (2022). A defect-based physics-informed machine learning framework for fatigue finite life prediction in additive manufacturing. *Materials & Design*, *222*, 111089.

[26] Wu, J., Lu, Y., Gao, H., & Wang, M. (2022). Cultivating historical heritage area vitality using urban morphology approach based on big data and machine learning. *Computers, Environment and Urban Systems*, *91*, 101716.

[27] Seydi, S. T., Hasanlou, M., &Chanussot, J. (2022). A quadratic morphological deep neural network fusing radar and optical data for the mapping of burned areas. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *15*, 4194-4216.

[28] Diao, C., Zhang, D., Liang, W., Li, K. C., Hong, Y., &Gaudiot, J. L. (2022). A novel spatial-temporal multi-scale alignment graph neural network security model for vehicles prediction. *IEEE Transactions on Intelligent Transportation Systems*, *24*(1), 904-914.

[29] Pierezan, J., dos Santos Coelho, L., Mariani, V. C., de Vasconcelos Segundo, E. H., &Prayogo, D. (2021). Chaotic coyote algorithm applied to truss optimization problems. *Computers & Structures*, *242*, 106353.