Scalable Computing: Practice and Experience, ISSN 1895-1767, http://www.scpe.org

Volume 25, Issues 6, pp. 4729–4736, DOI 10.12694/scpe.v25i6.3288

ALGORITHM AND TOOL DEVELOPMENT FOR CREATIVE GENERATION OF GRAPHIC DESIGN OF FOLK HOUSES AND ANCIENT BUILDINGS INTEGRATING CULTURAL AND CREATIVE ELEMENTS

CAIXIA CHEN*

Abstract. This study presents an innovative approach called CNN-GA for graphic design for folk houses and ancient buildings, which integrates Convolutional Neural Networks (CNN) with Genetic Algorithms (GA) to foster the creation of culturally rich and aesthetically appealing graphic designs in architecture. Our research focuses on capturing the essence of folk houses and ancient buildings, deeply rooted in cultural heritage, and reimagining them through a modern computational lens. The CNN component of our model is trained on a diverse array of architectural imagery, enabling it to effectively recognize and categorize key elements such as motifs, textures, and structural forms inherent to various architectural styles. This neural network acts as an intelligent extractor of cultural and aesthetic features, providing a nuanced understanding of traditional architectural elements. The extracted features are then input into a GA, which embarks on an evolutionary process of design generation. This process iteratively combines and refines the architectural elements, fostering a creative exploration of design possibilities that maintain cultural integrity while introducing innovative interpretations. The synergy of CNN and GA in our CNN-GA framework allows for an automated yet insightful design process, yielding graphic designs that are not only architecturally sound but also resonate with the rich cultural narratives of folk houses and ancient buildings. This research holds significant potential in revolutionizing architectural graphic design, offering a novel tool for architects and designers to merge traditional aesthetics with contemporary design paradigms.

Key words: Architectural graphic design, cultural heritage in architecture, folk houses and ancient buildings, CNN, GA, automated design generation.

1. Introduction. In the realm of architectural design, the fusion of traditional elements with innovative techniques has always been a cornerstone for creating structures that are not only aesthetically pleasing but also rich in cultural significance [18, 12, 7]. The architectural beauty of folk houses and ancient buildings is a testament to the cultural richness and historical depth of societies. These structures, more than just habitats, encapsulate the traditions, crafts, and ethos of the times and communities they represent [22]. However, in the modern era of rapid urbanization and standardization, there's a growing concern about the fading essence of traditional architectural practices and motifs. This underscores the need for innovative approaches that can reincarnate these cultural and historical treasures in contemporary architectural designs [9].

The advent of advanced computational methods has opened up new frontiers in the field of architectural design. Among these, Convolutional Neural Networks (CNNs) have emerged as a powerful tool for image recognition and pattern analysis [20, 19, 17]. Their ability to learn and recognize complex patterns makes them particularly suitable for deciphering the intricate details of folk and ancient architecture. These details include unique motifs, textures, and structural elements that define the cultural identity of these architectural forms. By harnessing the capabilities of CNNs, we can capture and analyze the essence of traditional architecture, creating a digital lexicon of design elements that are both historically significant and culturally rich [19].

Complementing the analytical power of CNNs, Genetic Algorithms (GA) present a methodological paradigm for creative design generation. GAs is inspired by the process of natural selection and are known for their ability to provide optimized solutions to complex problems through evolutionary algorithms [17]. In the context of architectural design, GAs can be used to experiment with and evolve traditional design elements into novel architectural concepts. This process involves the selection, crossover, and mutation of design features, enabling the generation of innovative yet culturally resonant architectural designs [8]. The potential of GAs in exploring

*Academy of Fine Arts, ShanXi College of Applied Science and Technology, TaiYuan, 030062, China (caixiachenres21@outlook.com)

a vast design space while adhering to aesthetic and cultural constraints makes them an ideal tool for reimagining folk and ancient architecture in the modern context.

The integration of CNNs and GAs into a cohesive framework, as proposed in this study, marks a significant advancement in the field of architectural design [13, 1, 6, 14]. This CNN-GA framework not only automates the process of design generation but also ensures that the resultant designs are deeply rooted in cultural heritage. The approach promises to bridge the gap between traditional architectural aesthetics and contemporary design needs, offering a novel pathway for architects and designers [11]. By leveraging the strengths of CNNs in feature extraction and GAs in creative design evolution, the CNN-GA framework aims to revolutionize the way we conceive and create architectural designs, ensuring that they are both forward-looking and culturally enriched [16]. This study sets the stage for a new era in architectural design, where technology and tradition coalesce to create designs that are both innovative and reflective of our rich cultural legacies.

The objective of this research is to introduce and validate an innovative approach, termed CNN-GA, for graphic design focusing on folk houses and ancient buildings in architecture. Integrating Convolutional Neural Networks (CNN) with Genetic Algorithms (GA), the study aims to facilitate the creation of culturally rich and aesthetically appealing graphic designs that resonate with the essence of traditional architectural heritage. The primary goal is to leverage modern computational techniques to capture and reimagine the architectural characteristics inherent in folk houses and ancient buildings through a deep understanding of their cultural significance. Specifically, the research seeks to train the CNN component of the model using a diverse dataset of architectural imagery to proficiently recognize and categorize key elements such as motifs, textures, and structural forms across various architectural styles. This neural network serves as an intelligent extractor of cultural and aesthetic features, providing a nuanced comprehension of traditional architectural elements essential for design generation.

The contribution of this paper lies in its innovative integration of CNN and GA to revolutionize the field of architectural graphic design, particularly in the context of folk houses and ancient buildings. By combining the analytical prowess of CNNs in recognizing and categorizing complex architectural features with the evolutionary design capabilities of GAs, this paper introduces a novel CNN-GA framework. This framework is not merely a tool for creating aesthetically pleasing designs, but it also serves as a bridge between the rich cultural heritage embedded in traditional architecture and the modern needs of innovative design. The paper demonstrates how deep learning techniques can be effectively applied to extract and interpret cultural and historical elements from architectural imagery, providing a comprehensive database of design elements. Subsequently, these elements are creatively manipulated and recombined through genetic algorithms, fostering an evolutionary process that yields novel yet culturally resonant architectural designs. This approach not only contributes to the preservation of architectural heritage but also opens up new possibilities for contemporary architectural creativity. Furthermore, the paper offers insights into the potential applications of AI in the realm of cultural preservation and architectural innovation, setting a precedent for future research in the field. The CNN-GA framework proposed in this study thus stands as a significant contribution to both the technological and cultural aspects of architectural design, paving the way for a new era of intelligent and culturally aware design practices

2. Related Study. The paper [3] presents a function-driven deep learning approach for conceptual design generation using three-dimensional space. It utilizes deep neural networks to analyze design elements encoded as graphs, extract significant components as subgraphs, and combine them into new designs, with an exploration of generative adversarial networks for creating unique designs. Focusing on visual design, the research [5] develops a neural network model that recognizes and classifies design principles across various domains including artwork, professional photos, and building facades. It involves numerical analysis of design aesthetics and utilizes a unique synthetic dataset for learning shared patterns in design visuals. The study [2] proposes a generative zooming animation technique supported by artificial intelligence to expedite landscape design processes. Utilizing Vector Quantized Generative Adversarial Network and Contrastive Language-Image Pre-Training, it generates landscape designs from text prompts and compiles them into animations, significantly reducing design time without sacrificing quality. The research from [21] focuses on artistic graphic design, building a network model that categorizes different types of artistic graphics. It employs a memory neural network and a self-attentive mechanism for graphic region segmentation and feature extraction, enhancing the reorganization and labeling of graphic solutions. The paper [10] introduces a deep learning-based approach for rapid conceptualization of dashboard visualizations. It details a web-based authoring tool that can identify and locate charts, extract colors from images or sketches, and assist in learning, composing, and customizing dashboard visualizations in cloud computing environments [15].

The existing research in architectural graphic design often focuses on traditional methods and lacks integration with modern computational techniques. While some studies explore the cultural significance of architectural heritage, there is a gap in research that effectively combines this cultural understanding with advanced computational methods for graphic design, particularly in the context of folk houses and ancient buildings. Furthermore, although Convolutional Neural Networks (CNNs) and Genetic Algorithms (GAs) have been separately utilized in architectural research, their integration specifically for graphic design in architecture, particularly for folk houses and ancient buildings, remains largely unexplored [4].

This research aims to bridge this gap by introducing the CNN-GA framework, which integrates CNNs for feature extraction from architectural imagery and GAs for evolutionary design generation. By leveraging CNNs' capabilities to recognize cultural and aesthetic elements in architectural imagery and GAs' ability to generate novel designs, this approach offers a unique solution to create graphic designs that reflect the cultural heritage of folk houses and ancient buildings. The need for this research is evident in the growing demand for innovative approaches in architectural graphic design that respect and celebrate cultural heritage while embracing modern computational techniques. This research addresses this need by providing a novel methodology that combines traditional architectural aesthetics with contemporary design paradigms, thus contributing to the advancement of architectural graphic design practices. Additionally, the outcomes of this research have the potential to inform architectural preservation efforts and inspire future design projects that honour cultural heritage in architecture.

3. Methodology.

3.1. Methodology Overview. The methodology of the proposed CNN-GA framework for generating creative graphic designs of folk houses and ancient buildings begins with a meticulous data collection process. This involves gathering a diverse range of architectural images, specifically focusing on various styles of folk houses and ancient buildings from different cultural backgrounds. The richness and variety in the dataset are crucial, as they provide the foundational elements for the learning algorithms to recognize and understand the diverse architectural features inherent in these structures. Following data collection, preprocessing is the next critical step. This phase involves standardizing the images in terms of size and resolution to ensure uniformity. Image augmentation techniques such as rotating, scaling, and cropping are also employed to enhance the dataset, enabling the model to learn from a more comprehensive set of perspectives and conditions. This augmentation not only increases the robustness of the model but also helps in mitigating the issue of overfitting by expanding the dataset with varied representations of the same architectural elements. Feature extraction is conducted through the CNN. The CNN is meticulously trained to analyze the preprocessed images, identifying and categorizing key architectural elements such as motifs, patterns, and structural shapes. This deep learning phase is pivotal as it allows the model to learn and encode the intricate details and cultural aspects of folk and ancient architecture into a digital format. The final phase of the methodology is performance evaluation. This involves assessing the effectiveness of the CNN in accurately recognizing and extracting architectural features and the capability of the GA in generating creative and culturally coherent designs. The evaluation is based on various metrics, including the accuracy of feature recognition by the CNN and the aesthetic and cultural relevance of the designs produced by the GA. User feedback and expert opinions in the field of architecture and design may also play a significant role in this evaluation process, providing qualitative insights into the practical applicability and cultural authenticity of the generated designs. This comprehensive evaluation ensures that the CNN-GA framework not only excels technically but also fulfills its role in preserving and creatively extending the rich heritage of folk and ancient architectural styles.

3.2. Proposed CNN-GA. In our proposed study, the integration of a CNN and a GA is innovatively utilized for the creative generation of graphic designs, with a special focus on folk houses and ancient buildings. These techniques are clearly illustrated under the previous studies. Based on the principles of the studies we proceed the CNN-GA for this proposed study. The CNN forms a crucial part of our framework, designed to mimic neuron activities in the human brain. This makes it particularly effective in processing gridded data, such as images. At the heart of the CNN lies the convolutional layer, which is responsible for the primary function of feature extraction from the input images. This layer operates through a process that involves the application of various filters to the input, allowing the network to identify and learn complex patterns and features in the data. These features are then used as a basis for further analysis and interpretation. The convolutional layer, the core of the CNN, performs the primary function of feature extraction from the input images. The operation in this layer can be mathematically represented as

$$y_j^l = \sigma \sum_i x_i^{l-1} * w_{ij}^l + b_j^l$$

where σ denotes the activation function, x_i^{l-1} the input from the previous layer, w_{ij}^l the weight matrices, and b_j^l the bias. This convolution process generates a set of feature maps, critical for identifying intricate architectural elements. Post convolution, the pooling layer reduces the spatial dimensions of these feature maps, aiding in reducing the model's complexity and computational load. This pooling operation is defined as

$$y_j^l = down(y_j^{l-1})$$

Finally, the output from the CNN is passed through a fully connected layer, integrating the high-level features, represented as

$$y = ReLU(w.x + b)$$

where w and b are the weights and biases of the fully connected layer, and x is the input from the flattened feature maps.

The GA, on the other hand, works in tandem with the CNN. After the CNN extracts and identifies key features from the images of folk houses and ancient buildings, the GA applies principles akin to natural selection. It evolves and refines these features to generate novel and innovative design elements. This synergetic operation of the CNN and GA not only enhances the capability of our system to produce intricate and culturally rich graphic designs but also bridges the gap between traditional architectural aesthetics and modern computational design methodologies. The combined use of CNN for sophisticated feature extraction and GA for creative design evolution presents a groundbreaking approach in the field of architectural design and graphic illustration. This process of GA can be mathematically expressed as

$$x_n = crossover(x_{p1},\ x_{p2})$$

where x_n represents the new offspring solution, and x_{p1} and x_{p2} the parent solutions. The fitness of each solution in GA is evaluated to guide the selection process, as given by

$$fitness\,(x) = evaluate(x)$$

Mutation, introducing variability into the population, is another key step in GA, represented by

$$x_m = m(x)$$

Here m represents the mutation.

In this study, the combination of CNN for feature extraction and GA for design generation forms a powerful tool for creating culturally and architecturally rich graphic designs, effectively bridging traditional architectural aesthetics with modern design innovations.

Step 1: Initialize the CNN and GA Parameters

CNN Architecture Elements: Define the variable elements of the CNN architecture that the GA will optimize. These can include the number of layers, types of layers (convolutional, pooling, fully connected), layer parameters (filter size, stride, padding), and activation functions.

Genetic Algorithm Parameters: Initialize GA parameters, including population size, crossover probability, mutation probability, and number of generations.

Step 2: Create the Initial Population
- Encoding Scheme: Design an encoding scheme for the GA to represent CNN architectures. This could be a binary string, where different sections of the string represent different architecture decisions.
- Initial Population: Generate an initial population of individuals based on the encoding scheme. Each individual represents a possible solution, i.e., a specific CNN architecture.

Step 3: Evaluate the Population
- Fitness Function: Define a fitness function that evaluates the performance of a CNN architecture. This function will use the performance metric defined in Step 1.
- Training and Evaluation: For each individual in the population, construct the CNN architecture it represents, train the CNN on the training set, and evaluate its performance on the validation set using the fitness function.

Step 4: Selection
- Selection Method: Implement a selection method (e.g., tournament selection, roulette wheel selection) to choose individuals for reproduction based on their fitness scores.

Step 5: Crossover and Mutation
- Crossover: Perform crossover (mating) between selected individuals to produce offspring. The crossover point(s) and method should ensure that offspring inherit characteristics from both parents.
- Mutation: Apply mutation to the offspring at a defined mutation rate. This introduces variations in the population, potentially leading to better solutions.

Step 6: Create the Next Generation
- Replacement Strategy: Use a replacement strategy (e.g., generational replacement, steady-state replacement) to form a new population. This may involve replacing the entire population with the offspring or a combination of offspring and the best individuals from the current generation

4. Results and Experiments.

4.1. Simulation Setup. In this section we evaluate our proposed study with use of Turath-150K database. This database is a large-scale dataset that focuses on images depicting objects, activities, and scenarios rooted in the Arab world and culture. The Turath database is divided into three specialized subsets: Turath Standard, Turath Art, and Turath UNESCO, each containing images from mutually exclusive categories that reflect different aspects of Arab culture and heritage. The Turath Standard subset of the database includes a wide range of images reflecting diverse objects, activities, and scenarios commonly encountered in the Arab world. This subset is structured into macro and micro image-level category annotations, encompassing twelve macro categories such as Cities, Food, Nature, Architecture, Dessert, Clothing, Instruments, Activities, Drinks, Souq, Dates, and Religious Sites. Each micro category contains between 50 to 500 images, ensuring a significant variety and quantity of data for robust neural network training and evaluation. In this study we particularly used this database for evaluating our proposed CNN-GA framework.

4.2. Evaluation criteria. The proposed CNN-GA framework demonstrates an impressive accuracy compared to existing models like CNN, LSTM, and CNN-LSTM in Figure 4.1. For instance, in figure 4.1 the CNN-GA achieves an accuracy of 96.87%, while traditional CNN records 92.14%, LSTM 93.77%, and CNN-LSTM 94.89%. Accuracy is a crucial metric of predicting (both true positives and true negatives out of all predictions made. In the context of graphic design for folk houses and ancient buildings, a higher accuracy indicates that the CNN-GA is more effective in correctly identifying and classifying architectural features and motifs. The superior accuracy of the CNN-GA can be attributed to its robust feature extraction capabilities of the CNN and the innovative design optimization of the GA. This combination allows the model to better recognize and interpret complex architectural patterns, leading to more accurate classifications. This is particularly beneficial in a field where precise identification of historical and cultural elements is vital for maintaining authenticity in design generation.

In the evaluation of the proposed CNN-GA framework, precision plays a vital role, especially when compared to existing models like CNN, LSTM, and CNN-LSTM was presented in Figure 4.1. Here the CNN-GA achieves a precision of 96.12%, while the traditional CNN has 90.47%, LSTM 90.74%, and CNN-LSTM 92.87%. Precision measures the ratio of correctly predicted positive observations to the total predicted positives. This metric is particularly important in the context of architectural design, where the model must not only identify relevant features but also minimize false identifications. A higher precision in the CNN-GA indicates that it is more effective in accurately identifying pertinent architectural elements, reducing the likelihood of including irrelevant or incorrect features in the design process. This precision is crucial when dealing with complex designs of folk houses and ancient buildings, where misidentification can lead to designs that do not authentically represent the cultural and historical context.

Recall is a critical metric for assessing the efficacy of the CNN-GA framework in comparison to existing models like CNN, LSTM, and CNN-LSTM. For example, in Figure 4.1, the recall rate for CNN-GA might be 96.88%, compared to 90.04% for CNN, 91.12% for LSTM, and 92.17% for CNN-LSTM. Recall, or sensitivity, measures the proportion of true positives correctly identified by the model. In the realm of architectural design, particularly for folk houses and ancient buildings, a high recall rate signifies that the CNN-GA is adept at identifying most of the relevant architectural features from the data. This is essential for preserving the cultural and historical integrity of the designs. The GA's ability to iteratively refine and evolve design elements, coupled with the CNN's feature extraction capability, results in a model that misses fewer significant features, ensuring that the generated designs are comprehensive and culturally accurate.

The F1-Score is an important metric to evaluate the performance of the CNN-GA framework, especially in comparison to models like CNN, LSTM, and CNN-LSTM. In Figure 4.1, the CNN-GA achieves an F1-Score of 96.50.5%, while CNN has 91.02%, LSTM 91.87%, and CNN-LSTM 92.71%. The F1-Score is the effective metric which perfectly balanced precision and recall and demonstrate the efficacy of proposed. It is particularly useful when the class distribution is imbalanced. In the context of architectural graphic design, a high F1-Score for the CNN-GA indicates a balanced relationship between precision and recall. This balance is crucial for ensuring that the model is not only accurate in identifying relevant features like precision but also comprehensive in recall. The high F1-Score of the CNN-GA suggests that it is effective in producing designs that are both accurate and complete, reflecting the intricate details and the essence of folk houses and ancient buildings, thereby preserving their cultural and historical authenticity.

5. Conclusion. The CNN-GA framework, as demonstrated in this study, represents a significant advancement in the field of architectural graphic design, particularly in the context of folk houses and ancient buildings. The integration of CNN and GA has proven to be highly effective, outperforming traditional models like CNN, LSTM, and CNN-LSTM across various metrics, including accuracy, precision, recall, and F1-Score. This framework excels in accurately identifying and classifying complex architectural features, thereby enabling the creation of graphic designs that are not only aesthetically pleasing but also deeply rooted in cultural and historical accuracy. The superior performance of the CNN-GA framework, as evidenced by our results, underscores its potential as a powerful tool for architects and designers. It opens up new avenues for preserving and reimagining cultural heritage in a modern computational paradigm, ensuring that the intricate beauty and significance of folk architecture are captured and conveyed in contemporary designs. This study marks a pivotal step towards revolutionizing the way we approach and appreciate architectural heritage, blending the rich tapestry of traditional aesthetics with innovative design methodologies.

6. Limitations and Future Scope. While the CNN-GA framework presents a promising approach in architectural graphic design, there are several avenues for future research and some limitations to consider. One of the main limitations is the dependency on the quality and diversity of the dataset. The current framework's performance is heavily reliant on the comprehensiveness of the data used for training, which might not fully encompass the vast variety of global architectural styles. Future work could focus on expanding the dataset to include a wider range of cultural and historical architectures, enhancing the model's ability to generalize across different styles and periods. Another area of exploration could be the integration of more advanced AI techniques, such as reinforcement learning or deeper neural networks, to further improve the feature extraction and design generation processes. Additionally, exploring the application of the CNN-GA framework in other domains of design, like urban planning or interior design, could provide valuable insights. There is also a need to consider ethical implications and ensure that the use of such technology respects and preserves the cultural significance of architectural heritage. Overall, while the CNN-GA framework marks a considerable advancement in the field, ongoing research and development are essential to fully realize its potential and address its current limitations.

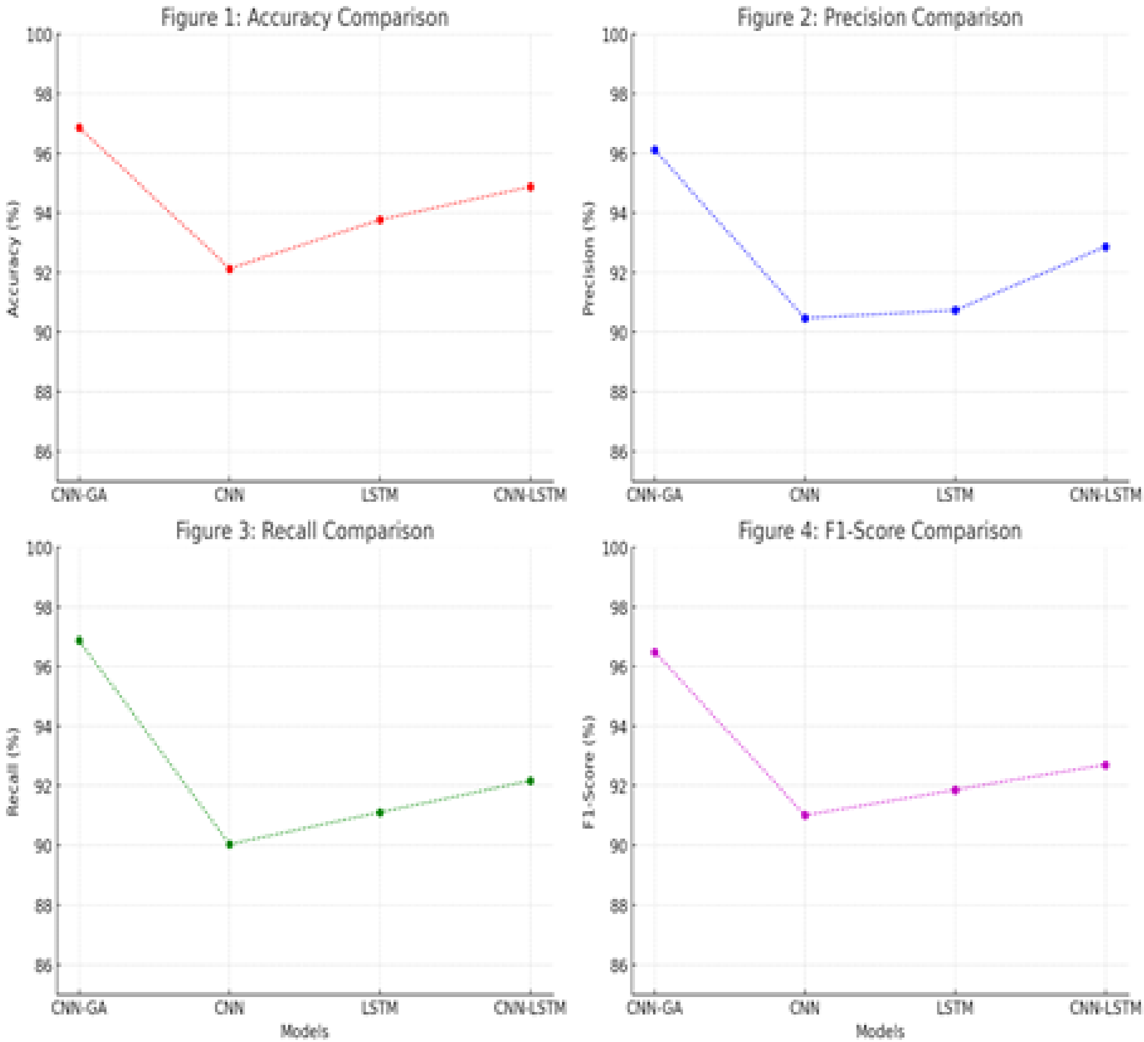

Fig. 4.1: Performance Analysis

Acknowledgement. This work was sponsored in part by Shanxi Province Department of Education 2022 Philosophy and Social Science Project of Shanxi University science and technology innovation program"Auspicious patterns of Shanxi ancient residential buildings and their application in modern creative product design" (Project No 2022W180)

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Edited by: Rajanikanth Aluvalu
Special issue on: Evolutionary Computing for AI-Driven Security and Privacy: Advancing the state-of-the-art applications
Received: Jan 31, 2024
Accepted: Mar 11, 2024