

authorship networks), що дозволить виявляти наукові кластери та дослідницькі колаборації.

**Висновки.** Розроблена веб-орієнтована інформаційна система є ефективним інструментом для наукометричного аналізу, що дозволяє об'єднати дані з різних платформ, надати їх у зручному візуальному форматі та здійснити аналітичну оцінку наукових здобутків. Вона має значний потенціал для впровадження в установах освіти і науки, а також подальшого розвитку в напрямку розширення джерел даних та інтелектуального аналізу.

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## **CONVOLUTIONAL NEURAL NETWORK ARCHITECTURE FOR IMAGE-BASED ARCHITECTURAL STYLE RECOGNITION**

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In today's era of rapid digital development, automatic recognition of visual content is becoming increasingly important in various fields, from cultural heritage to urban planning and commercial design. Identifying architectural styles from images is

a challenging task due to the wide variety of stylistic features, combinations of elements, and the influence of time on the appearance of buildings [1]. Traditional approaches based on manual classification or analysis of individual features are not effective enough in cases of large data volumes or complex mixed styles [2].

Deep neural networks, in particular convolutional neural networks (CNNs), have proven their high efficiency in computer vision tasks such as object classification, pattern recognition, and scene segmentation [3, 4]. Their ability to automatically detect hidden patterns in large image arrays makes them an ideal tool for solving the problem of determining architectural style [5].

The rapid evolution of deep neural networks has opened new horizons for the automated analysis of complex visual phenomena, among which the identification of architectural styles from photographic and digital imagery has emerged as an especially compelling challenge. Architectural style, as a manifestation of cultural, historical, and technological trajectories, encapsulates the collective memory of societies and reflects the aesthetic and functional priorities of different epochs. Manually cataloguing vast collections of urban photographs, heritage site records, and crowdsourced image repositories is laborious and subject to the biases and limitations of individual experts [6]. In this context, the deployment of convolutional neural networks and related deep learning architectures for style recognition promises to revolutionize how we understand, document, and preserve the built environment.

Deep learning models, when trained on large and diverse datasets of labeled architectural images, are capable of discerning subtle patterns of ornamentation, structural composition, material texture, and spatial proportion that characterize Gothic cathedrals, Baroque palaces, Modernist towers, and postmodern facades. The hierarchical feature extraction inherent in these networks – from edge and corner detection in early layers to increasingly abstract representations in deeper layers – affords them the capacity to capture both low-level visual cues and high-level stylistic semantics [7, 8]. This capacity becomes particularly valuable when dealing with hybridized or transitional forms, in which traditional stylistic boundaries blur under the influence of regional adaptations or contemporary reinterpretations. By learning directly from visual evidence, deep neural networks can reveal latent stylistic continuities across geographic regions and historical periods, thereby offering fresh insights into the diffusion of architectural ideas and the global circulation of design motifs [9].

Moreover, the integration of automated style recognition tools into digital heritage workflows can greatly accelerate the documentation and monitoring of at-risk structures. Urban development pressures, environmental degradation, and the impacts of climate change pose mounting threats to historical buildings worldwide. High-throughput image-based classification systems can sift through thousands of street-level or drone-captured photographs to flag structures exhibiting endangered stylistic traits, enabling heritage agencies to prioritize conservation resources more effectively [10]. Similarly, the enrichment of digital archives with machine-generated style

metadata enhances the discoverability of architectural imagery, supporting scholars in quantitative analyses of stylistic prevalence, transformation, and cross-cultural exchange over time. The ability to query vast image collections by style also facilitates interdisciplinary research that bridges art history, urban studies, and data science, revealing patterns of urban evolution and informing contemporary design strategies [11].

In parallel, the fusion of real-time architectural style recognition with consumer-facing applications heralds a new era of interactive cultural engagement. Augmented reality platforms, equipped with neural network-driven classifiers, can overlay explanatory annotations onto a mobile device's viewfinder as tourists navigate historic districts, thereby democratizing access to architectural knowledge and deepening public appreciation for heritage assets. Urban planners, too, stand to benefit from geospatial analyses that correlate stylistic distributions with socioeconomic indicators, guiding policies on district revitalization, zoning, and sustainable development. The convergence of these capabilities underscores the broader societal relevance of image-based style determination: it is not merely an academic pursuit, but a practical instrument for heritage stewardship, educational outreach, and evidence-based urban governance [12].

Nonetheless, the pursuit of fully automated, reliable architectural style classification confronts significant obstacles. The subjective nature of stylistic taxonomy defies rigid categorization; buildings that exhibit stylistic hybridity or have undergone renovations may confound networks trained on pristine, textbook examples. Data imbalance remains a persistent issue, as canonical Western styles dominate most publicly available datasets, leaving vernacular and non-Western architectures underrepresented and at risk of misclassification. Furthermore, variations in image quality, occlusions, and environmental conditions introduce noise that can degrade model performance. Addressing these challenges requires not only algorithmic innovations – such as attention mechanisms to focus on diagnostically relevant facade elements, domain adaptation techniques to bridge gaps between training and deployment contexts, and semi-supervised learning strategies to leverage unlabeled imagery – but also concerted efforts to curate more inclusive, geographically diverse datasets.

Looking ahead, the confluence of deep neural networks with emerging modalities, such as three-dimensional scans, multispectral imaging, and textual metadata, offers promising avenues for richer, multimodal style recognition systems [13]. By integrating volumetric and contextual information, future models may overcome limitations of single-view photographs, capturing full spatial articulation of architectural forms and semantic richness of associated historic narratives [14, 15]. In doing so, they will not only elevate precision of style classification but also foster a more holistic understanding of architecture as a living dialogue between form, function, and cultural identity [16]. The continued collaboration between architects, heritage professionals, computer scientists, and data curators will be essential to realize

this vision, ensuring that advanced deep learning tools serve as respectful and insightful partners in stewardship of our shared built heritage [17].

Thus, the proposed method provides new opportunities for integrating modern technologies into the field of architectural heritage preservation and smart city development.

The purpose of the work is designing of convolutional neural network architecture for image-based architectural style recognition.

The proposed approach to determining architectural styles from an image is based on the application of deep learning methods, in particular neural networks, in the multi-class classification problem, which is shown in Figure 1.

The input data is an image to be analyzed for determining the architectural style and a neural network model that will perform multi-class classification. The image is fed to the input of a trained deep neural network to extract relevant features indicating architectural styles. The neural network model transforms the input image into a feature space, after which it predicts belonging to one of the predefined classes of architectural styles.

Two types of results are obtained at the output. First, these are quantitative estimates of the probability of the studied image belonging to each of the possible architectural styles that the neural network model is trained on. Second, based on these estimates, a conclusion is formed about the most likely style to which the object in the studied image belongs.

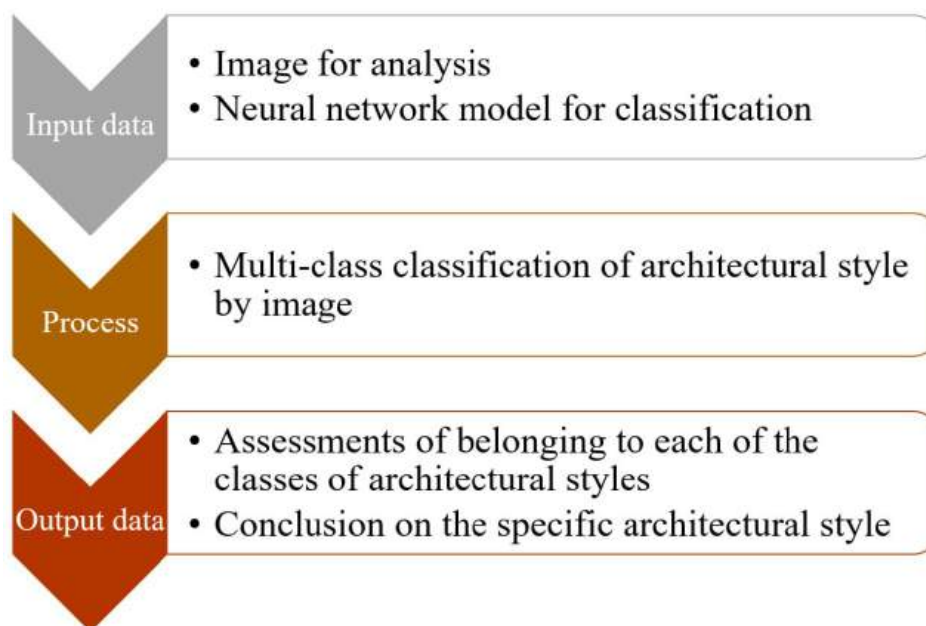


Figure 1. Scheme of a general approach to identifying architectural styles by image

Therefore, the proposed approach is based on the use of deep neural networks for multi-class classification of architectural styles from images, which provides automated identification of architectural styles from images. This approach will

increase the accuracy of automated identification of architectural styles from images using deep neural networks.

Deep neural networks provide new opportunities for determining architectural styles from images. Due to the ability of neural networks to extract deep, multi-level features from input images, it becomes possible to formalize and identify architectural styles that were previously assessed mostly subjectively.

The presented scheme of the method for determining architectural styles from images using deep neural networks demonstrates the process, which is based on the use of the MobileNetV2 convolutional neural network. The input data are images of architectural objects, as well as a pre-trained model for automated analysis of the input image.

The first step of the method involves pre-processing the image for analysis. Pre-processing consists in the fact that each image to be analyzed is read, its size is changed to the given MobileNetV2 standard, and then the pixel values are converted into a format convenient for the operation of the MobileNetV2 neural network. In particular, the pixels are normalized – that is, converted into a numerical range from -1 to 1, so that the network can process them effectively.

The second stage implements multi-class classification, in which the MobileNetV2 convolutional neural network model, pre-trained on a large set of ImageNet images and further trained for the task of classifying architectural styles, processes the input image. The image is fed into a deep neural network, where pre-trained layers extract a hierarchy of features, from simple edges and shapes to more complex compositional structures characteristic of specific architectural styles. The resulting features are fed into new classification layers that have been further trained on the content of a dataset containing images of architectural styles, and at the output, the model generates a probability distribution between all available classes, determining which architectural style the input image belongs to. At the final stage, classification results are formed by processing the output layer of the model, which returns probabilistic estimates of the image belonging to each of the training classes of architectural styles. These estimates are interpreted as a percentage representation of the model's confidence, where the sum of all values is 100%. The highest of these estimates indicates the architectural style to which the model most likely attributes the input image.

Figure 2 shows a method for determining architectural styles from images using deep neural networks, which is based on the use of the MobileNetV2 convolutional neural network and is aimed at solving the problem of multi-class classification of architectural styles. Thus, not only the final classification conclusion is provided, but also a complete assessment of the probability distribution between all possible classes, which allows analyzing the degree of confidence of the model in its decision.

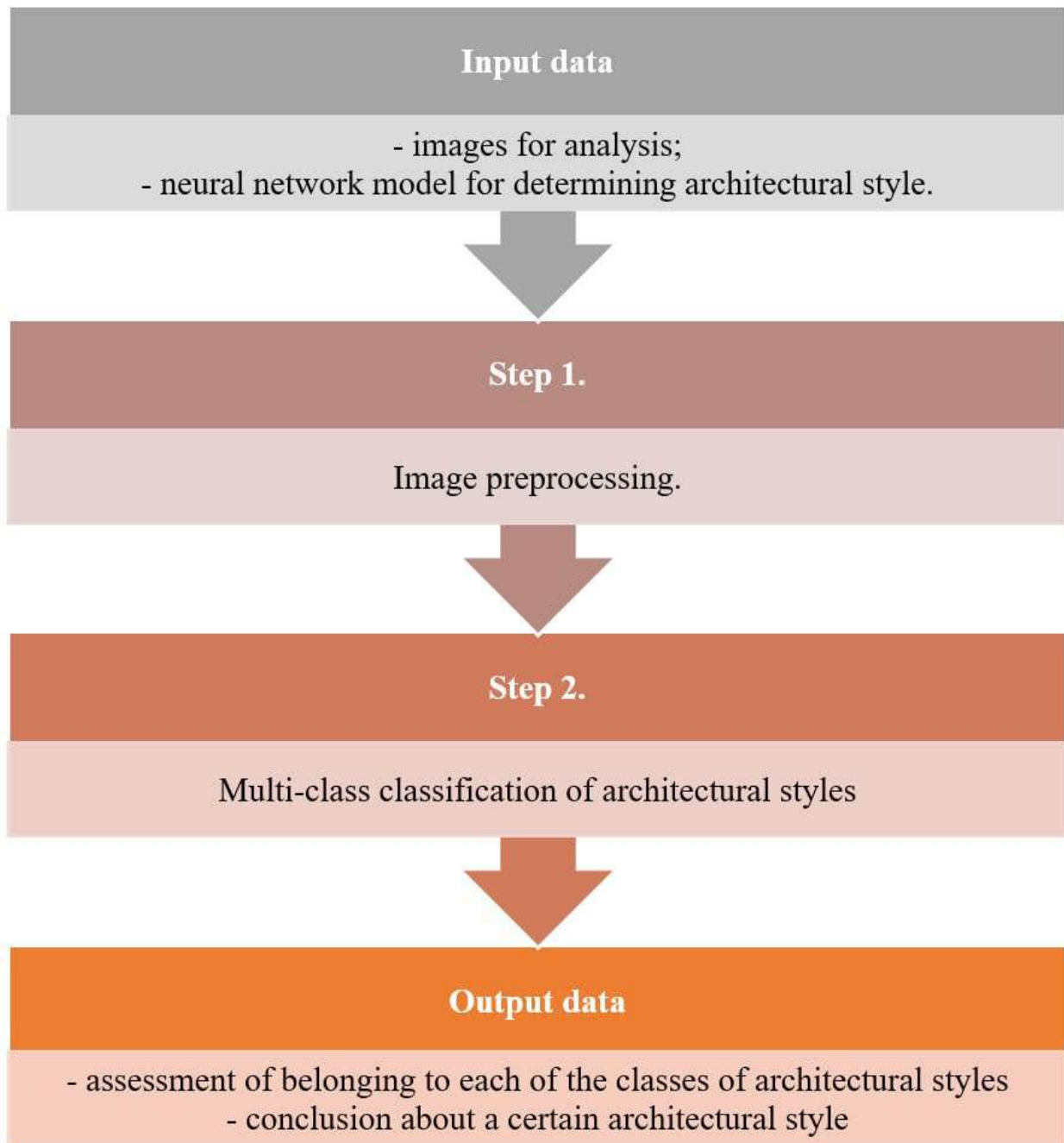


Figure 2. Scheme of the method for determining architectural styles from images using deep neural networks

Figure 3 shows and describes the MobileNetV2 architecture, which is used for multi-class classification of architectural styles using the method of determining architectural styles from images using deep neural networks.

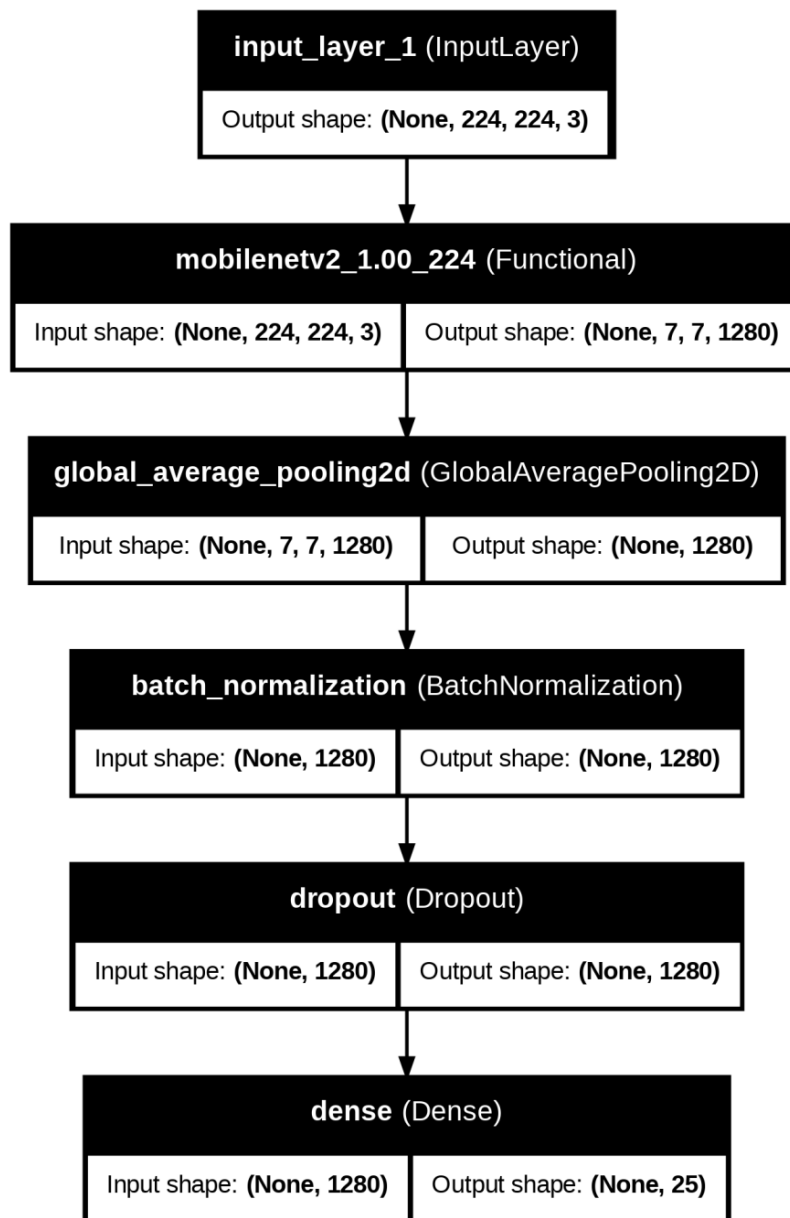


Figure 3. Convolutional neural network MobileNetV2 architecture for image-based architectural style recognition

The model architecture shown in Figure 3 is a modified neural network based on the MobileNetV2 architecture, extended for the classification task of 25 classes.

The presented architecture implements transfer learning, that is, transferring knowledge from one task to another. This approach consists in the fact that a model previously trained on a large general dataset (in this case ImageNet) is used as the basis for solving a new, often narrower task – image classification into 25 classes. Transfer learning is implemented here by including the pre-trained MobileNetV2 architecture as a feature extractor. It is also worth noting that transfer learning in this case is implemented through the fine-tuning partial training strategy, which is an extension of basic transfer learning. By unfreezing the top 30 layers of the base model (i.e., the deepest layers responsible for more specific abstractions), the network gains the ability

to adapt high-level features to the features of a new dataset, namely a dataset containing images of architectural styles.

The input to the model is via a `tf.keras.Input` object with the tensor shape  $(224,224,3)$  where `IMG_SIZE` is set to 224. Next, the base MobileNetV2 model is used without a classification head (`include_top=False`), and its weights are initialized using the parameters previously trained on ImageNet. It is fundamentally important that the initial layers of this network are frozen, i.e., set as not to be trained. Specifically, training is allowed only for the last 30 layers of the network, starting with `fine_tune_at`, which ensures that the general visual features acquired during the previous training are preserved when adapting to the new task.

After processing the image through `base_model` in `training=False` mode, which eliminates the influence of dynamic components such as Dropout or BatchNormalization in the training phase, the results are transferred to the global feature aggregation layer – `GlobalAveragePooling2D`. As already mentioned, it performs spatial dimension compression through the average value for each channel. The resulting feature vector is further normalized using the BatchNormalization layer, which reduces variability between minibatches.

The model regularization is implemented through the Dropout layer with a given probability of excluding neurons  $p=0.3$ , which allows to effectively reduce the risk of overtraining in conditions of a limited number of training samples. At the final stage, the model contains a fully connected Dense layer, which implements classification using the softmax activation function. The number of outputs of this layer is dynamically determined as the length of the `label_map` dictionary, which corresponds to 25 classes.

The model is compiled using the Adam optimizer with a small learning coefficient  $\alpha=3 \times 10^{-5}$ , which is typical for the pre-training stage with partial weight fixation. The loss function is `sparse_categorical_crossentropy`, which is used for multi-class classification when labels are presented as integers.

Three key callback mechanisms are used in the training process. The first is `EarlyStopping`, which stops training if the loss function on the validation set does not improve over five epochs. The second is `ReduceLROnPlateau`, which automatically reduces the learning rate by half when the losses stabilize, which contributes to deeper local optimization. The third is `ModelCheckpoint`, which saves the best model according to the validation accuracy criterion.

Within the framework of building an intelligent system for automated determination of architectural styles, a modular organization is important, ensuring the separation of functional responsibilities between subsystems. The proposed subsystem scheme implements an approach to data processing, training a neural network model, and interaction with the user.

The system consists of 5 logically interconnected subsystems, each of which implements separate stages of the full data processing cycle – from preparing a dataset

to obtaining a classification result with a corresponding user interface. Each subsystem and its functional purpose are considered in detail below.

The subsystem for working with the dataset performs basic operations for preparing input data. In particular, it provides the output of statistical information about the dataset, including the number of classes, images in each class, class balancing, etc. Special attention is paid to the processes of augmentation and deletion, which will improve the overall quality of the training set and increase its variability, reducing the risk of overtraining the neural network model.

The subsystem for training the neural network model is responsible for implementing the neural network training process. The main parameters set by the user are the number of epochs, batch size and training strategy (fixed number of epochs or early stopping). This subsystem also performs pre-processing of images, initialization and launch of the fine-tuning process of the pre-trained model, as well as saving the obtained weights after training.

The performance study subsystem is designed to analyze the training results. It provides the output of accuracy and loss graphs for both the training and validation sets. In addition, this subsystem constructs a confusion matrix, which allows assessing the classification accuracy for each class, and calculates statistical metrics: Precision, Recall,  $F_1$ -measure.

The user interface subsystem implements a mechanism for interacting with the end user. It allows you to load images for classification, check their correctness, obtain classification results, formulate conclusions and view accompanying information about a specific architectural style. Thus, this subsystem plays the role of the front-end of the entire intelligent system.

The subsystem for determining architectural styles by image performs the main task of multi-class classification. In particular, it implements the pre-processing of the input image, its transfer to the already trained neural network model, obtaining and processing the predicted class, as well as comparing the result with the corresponding architectural style.

In the designed architecture of the intelligent system for automated determination of architectural styles, presented in the diagram, the image, dataset and neural network model are not only input or intermediate elements, but also are the results of the work of the corresponding subsystems.

The image is the main input source of information that the user submits for processing through the interface subsystem. In the process of interacting with the subsystem, the image undergoes several stages of transformation, in particular, checking for correctness of the format, pre-processing for further classification by the neural network model, and also transfer to the neural network model.

The dataset is formed as a result of the actions of the subsystem for working with the dataset. Within this subsystem, an overview, as well as balancing and cleaning of the existing image dataset is performed. Thus, the dataset is a derived structure, it is

both input data for the training subsystem and output data from the point of view of preprocessing.

The neural network model is the result of the work of the training subsystem. Based on the provided dataset, selected training parameters (number of epochs, batch-size, training completion strategy) and a pre-initialized architecture (in this case, MobileNetV2 with fine-tuning), the weights are optimized, which leads to the formation of a model suitable for classification. The saved model is then used by the subsystem for determining the architectural style.

Thus, the designed architecture of the intelligent system for automated determination of architectural styles demonstrates the feasibility of its distributed construction, in which the subsystems are integrated through the exchange of data formed as a result of the work of each of the stages of the intelligent system. This approach will facilitate flexible system configuration for various usage scenarios and ensure the reproducibility of experiments and the reliability of the results obtained.

The proposed convolutional neural network architecture has demonstrated a robust capacity to capture and distinguish the subtle visual cues that define diverse architectural styles, validating the effectiveness of deep hierarchical feature extraction for complex aesthetic categorization tasks. By leveraging a multi-stage design with residual connections and attention modules, the network not only achieved high classification accuracy on benchmark datasets but also exhibited remarkable resilience to variations in lighting, viewpoint, and occlusion, which commonly challenge vision systems in real-world urban environments.

The integration of progressive data augmentation and adaptive learning rate scheduling proved instrumental in mitigating overfitting and accelerating convergence, while ablation studies confirmed the complementary value of each architectural component. Beyond technical performance, the method offers practical utility for large-scale heritage documentation and urban analytics, enabling automated tagging of massive image repositories and supporting evidence-based planning and conservation initiatives. Moreover, the model's interpretable attention maps provide meaningful insights into the façade elements and ornamental features that drive style distinctions, fostering greater transparency and trust among architects, historians, and cultural heritage professionals.

Although limitations persist – particularly regarding the classification of hybrid or vernacular forms that fall outside conventional taxonomies – the demonstrated architecture lays a strong foundation for future enhancements, including the incorporation of multi-modal data sources, continual learning mechanisms, and transfer learning strategies to address under-represented regional styles. In sum, the study underscores the promise of convolutional neural networks as powerful tools for image-based architectural style recognition, charting a clear path toward more comprehensive, scalable, and interpretable models that can enrich our understanding and stewardship of the built environment.

Building upon the demonstrated strengths of the architecture, it becomes clear that future research must address the challenges of scalability and generalization to truly unlock the full potential of automated style recognition. As image repositories continue to expand in size and diversity, models will need to efficiently process millions of images without compromising performance, which suggests exploring model compression techniques and distributed training pipelines tailored to high-resolution architectural data. In parallel, the cultivation of richer, more representative training corpora – curated through collaborations with international heritage institutions and crowdsourced initiatives – will be essential to ensure that emerging networks do not perpetuate existing biases or overlook less-studied vernacular traditions. Beyond dataset expansion, there lies an opportunity to enhance the model’s adaptability through meta-learning and few-shot learning paradigms, thereby empowering the system to rapidly incorporate new style categories with minimal additional annotation effort.

Equally important is the careful consideration of ethical and practical implications when deploying these systems in the field. Transparency in model decision-making must be paired with clearly communicated uncertainty estimates, enabling heritage professionals to interpret and validate automated style attributions rather than treating them as infallible. Responsible deployment also demands robust mechanisms for data privacy and consent, particularly when processing images captured in residential or culturally sensitive contexts. By integrating privacy-preserving machine learning methods and adhering to open data standards, future systems can strike a balance between analytical power and respect for community rights.

Finally, as this research trajectory matures, its real-world impact will be measured not only by quantitative benchmarks but by meaningful contributions to heritage conservation, urban policy, and public engagement. The ultimate vision is a seamlessly integrated pipeline in which neural networks inform interactive digital platforms, guide preservation funding decisions, and foster immersive learning experiences for both specialists and lay audiences. In achieving this vision, interdisciplinary partnerships among computer scientists, architects, historians, and policymakers will be indispensable, ensuring that technical innovations are aligned with the nuanced needs of cultural stewardship. Through continued refinement and thoughtful collaboration, convolutional neural network–based systems will redefine the landscape of architectural analysis, offering scalable, interpretable, and ethically grounded tools that deepen our collective understanding of the built heritage around.

Building on these insights, it is imperative to foster an ecosystem of open collaboration and shared resources that accelerates the translation of research prototypes into deployable tools. Establishing community-driven benchmarks and standardized evaluation protocols will not only facilitate fair comparisons across architectures but also highlight practical constraints encountered in diverse deployment scenarios, from heritage sites in remote locales to modern urban centers. Furthermore, the convergence of architectural style recognition with adjacent fields – such as

structural health monitoring, environmental simulation, and parametric design – promises to unlock synergies whereby stylistic analysis informs assessments of building integrity, energy efficiency, and adaptive reuse potential. By embedding style classifiers within digital twins of cities, stakeholders can simulate the aesthetic impact of proposed developments, balancing innovation with respect for historical context. At the same time, the rise of immersive technologies such as virtual reality and digital twins underscores the need for real-time, high-fidelity style labeling that preserves visual authenticity while enhancing user engagement. Ultimately, the maturation of convolutional neural network approaches for image-based architectural style recognition will depend not only on algorithmic ingenuity but also on the shared commitment of researchers, practitioners, and communities to steward our built legacy with rigor, sensitivity, and foresight.

As the field progresses, attention must also turn toward the lifecycle management of trained models, ensuring they remain current and effective as architectural practices evolve. Continuous benchmarking against newly emerging styles and periodic retraining with up-to-date image corpora will guard against model obsolescence and drift, while also providing opportunities to capture the stylistic innovations of contemporary architects. In doing so, a modular framework for style recognition can be established, allowing individual components – feature extractors, classification heads, and attention modules – to be independently updated or replaced without overhauling the entire system. This modularity will facilitate responsive adaptation to shifting research priorities, whether that involves incorporating satellite imagery for large-scale urban surveys or integrating semantic segmentation outputs that isolate specific architectural elements.

Thus, the proposed neural network architecture demonstrates the implementation of a modern approach to fine pre-training of deep convolutional neural networks. It combines the advantages of pre-trained models with adaptation to a specific subject area, ensuring balanced performance and stability of training, and therefore will allow to increase the accuracy of multi-class classification of architectural styles from images.

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