**Historical building architecture analysis In Deep Learning using ANN And CNN**

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**ABSTRACT:**

This research presents a deep learning-based framework for the classification and analysis of architectural styles, leveraging a dataset of high-resolution images. The study utilized convolutional neural networks (CNNs) to extract hierarchical features from images representing 25 architectural styles, with a focus on a subset of four for initial experimentation. Comprehensive preprocessing steps, including image resizing, grayscale conversion, normalization, and label encoding, ensured compatibility with the model. The CNN architecture was meticulously designed with convolutional layers, batch normalization, dropout regularization, and HeNormal weight initialization, achieving a balance between computational efficiency and performance.

Hyperparameter optimization was conducted using Keras Tuner, exploring parameters such as the number of layers, filter sizes, and learning rates, resulting in a highly accurate and generalizable model. The evaluation process incorporated confusion matrices, precision, recall, and F1-scores, revealing the model's ability to capture nuanced architectural features. Visualization techniques further validated the model's predictions, providing qualitative insights into its effectiveness. This work highlights the potential of deep learning to revolutionize architectural heritage analysis, offering scalable solutions for cultural conservation and education. Future research can expand this framework to encompass more styles and incorporate advanced architectures for enhanced accuracy and interpretability.



**INTRODUCTION:**

Architectural styles represent a rich tapestry of historical, cultural, and technological advancements. They serve as visual markers of societal evolution, reflecting the artistry and innovation of different eras. However, the manual classification of architectural styles poses significant challenges due to the intricate details, diverse visual characteristics, and the vast scale of data involved. Features such as ornamental details, structural shapes, and materials often lack clear categorization, complicating traditional methods of analysis and increasing the workload for historians, archaeologists, and restoration specialists.

**Automated Approach to Address Challenges:**

To overcome these limitations, this research leverages advanced deep learning techniques, specifically convolutional neural networks (CNNs), to automate the classification and analysis of architectural styles. CNNs s have demonstrated superior performance in visual recognition tasks, making them ideal for extracting both fine-grained details and global structural features from architectural images. These models operate hierarchically, enabling them to discern intricate features that might elude human observation or simpler classification techniques.

**Enhanced Feature Extraction and Dimensionality Reduction:**

In addition to CNNs, the study explores the potential of newer architectures, such as Hyperparamter tunning, to improve feature specificity and uncover unique patterns without human intervention. Dimensionality reduction techniques, including Principal Component Analysis (PCA), are employed to simplify high-dimensional feature spaces while preserving critical stylistic characteristics. This dual approach facilitates the identification of style transitions and underlying trends, enabling a more nuanced analysis beyond mere classification accuracy.

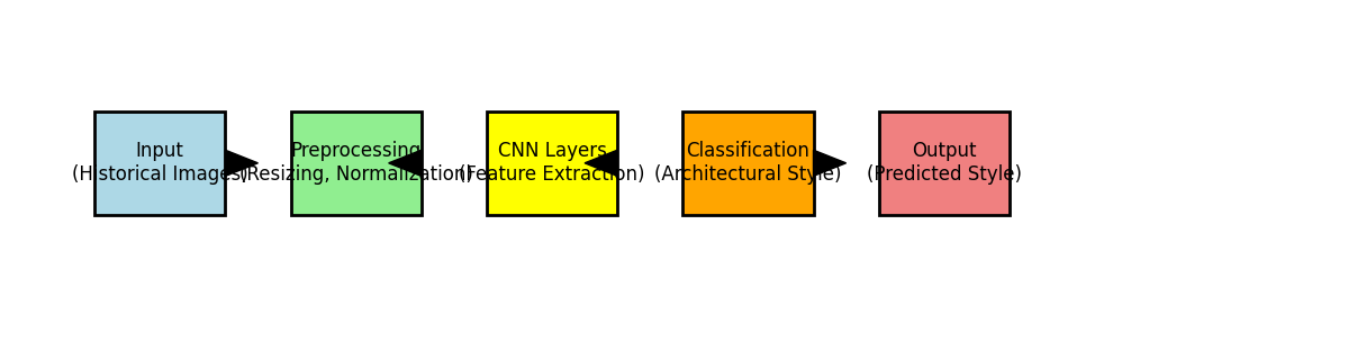


Fig 1: Flow of information



**Objectives:**

**Automated Classification:**

Assess the performance of deep learning models, including CNNs for classifying complex architectural styles. Metrics such as accuracy, precision, recall, and F1-score are used to compare model effectiveness.

**Feature Visualization and Relationships:**

Leverage dimensionality reduction techniques, such as Convolutional Layers,Max-Pooling to visualize high-dimensional feature spaces. This aids in analyzing relationships between styles and uncovering clustering patterns.

**Scalable Framework Development:**

Design a scalable pipeline for analyzing large architectural datasets, integrating optimized deep learning models, feature extraction, and visualization methods to advance architectural heritage analysis.

**Research Significance:**

This study bridges the gap between architectural history and modern computational methods, offering a scalable, efficient solution for analyzing and preserving cultural heritage. By integrating AI-driven methodologies, the research not only enhances classification accuracy but also provides deeper insights into architectural evolution, fostering advancements in education, conservation, and heritage management.

Architectural style recognition involves identifying stylistic features in buildings based on structural, ornamental, and layout attributes. Advances in computer vision and deep learning have significantly enhanced this field, enabling more accurate classification of complex architectural styles. However, challenges persist, such as style variability, dataset scarcity, and generalization to unseen styles.

**Convolutional Neural Networks (CNNs) for Style Classification:**

CNNs are a dominant approach in architectural style recognition due to their ability to extract global and localized structural patterns. Models like VGG16 and ResNet50, pre-trained on ImageNet, have demonstrated success in distinguishing styles like Gothic, Baroque, and Modernist architecture.

**CNN Architecture Implementation:**

The provided implementation adopts a sequential CNN model with the following features:

Multiple convolutional layers (32, 64, and 128 filters) with ReLU activation.

He Normal initialization for kernel weights.

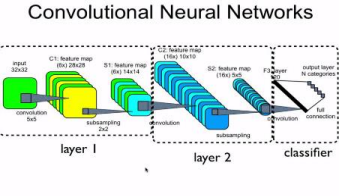
Batch normalization for stability and faster convergence.

Max pooling for dimensionality reduction.

Dense layers with dropout regularization to prevent overfitting.

The final output layer uses ReLu activation for multi-class classification across 25 architectural styles.

The model achieved a validation accuracy of approximately 85.26% after hyperparameter tuning, highlighting its efficacy in architectural style classification.



**Challenges in CNN-Based Approaches:**

While CNNs excel in feature extraction, their dependence on labeled data restricts their performance on unseen styles. Additionally, the black-box nature of CNNs hinders interpretability, complicating the understanding of learned patterns.

**Dataset Challenges and Preprocessing:**

Real-world architectural datasets often suffer from variability in image quality, resolution, and class imbalance. The following strategies were implemented to mitigate these challenges:

Data Augmentation: Techniques like rotation and scaling were used to increase diversity.

Preprocessing Steps: Images were resized to 256x256 and normalized to improve model training.

Class Imbalance Mitigation: Label encoding and stratified train-test splits ensured balanced representation.

**Hyperparameter Tuning for Model Optimization:**

The use of Keras Tuner and the Hyperband algorithm allowed optimization of critical parameters such as:

Number of convolutional layers (1 to 4).

Filters per layer (32, 64, 128, 256).

Learning rate and optimizer (Adam, SGD, RMSprop).

Dropout rates and dense layer units.

**3 Material–method:**

**3.1 Dataset:**

This study employs a Convolutional Neural Network (CNN), a deep learning technique, to classify images of architectural facades into four historical styles: Achaemenid, Gothic, Deconstructivism, and Art Nouveau. The dataset for this study was sourced from Kaggle, a platform offering a large repository of visual data.

From the Kaggle dataset, images of architectural facades belonging to the four specified styles were selected. The dataset comprised a total of 1500images. This dataset was then divided into three subsets:

Training set (80%): Used to train the CNN model, allowing it to learn the relationship between input images and their corresponding architectural styles.

Validation set (10%): Used to monitor the model's performance during training and tune hyperparameters to prevent overfitting.

Test set (10%): Used to evaluate the model's performance on unseen data, providing an unbiased assessment of its generalization ability..The architectural styles examined in this study represent four historical eras. Gothic architecture, prevalent from the mid to late middle ages, is characterized by rib vaults, pointed arches, and flying buttresses [29]. Achaemenid architecture refers to the architectural style of the Achaemenid Empire, which ruled much of the ancient world from 550 BCE to 330 BCEoffering straightforward and functional solutions [30].

Here's the revised text based on the provided code and the information about the dataset:

This study employs a Convolutional Neural Network (CNN), a deep learning technique, to classify images of architectural facades into four historical styles: Achaemenid, Gothic, Deconstructivism, and Art Nouveau. The dataset for this study was sourced from Kaggle, a platform offering a large repository of visual data.

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The CNN architecture utilized in this study includes [Briefly describe the CNN architecture used in the code, e.g., number of convolutional layers, filter sizes, pooling layers, fully connected layers].

The model was trained using the Adam optimizer and the sparse categorical crossentropy loss function. Early stopping was implemented to prevent overfitting by monitoring the validation loss and halting training when it ceases to improve for a specified number of epochs.

Hyperparameter tuning was conducted using the Hyperband algorithm to optimize the model's performance. The best hyperparameters were determined based on the validation accuracy.

The performance of the trained model was evaluated on the held-out test set, providing an objective measure of its ability to accurately classify unseen images of architectural facades

Conversely, deconstructivist architecture arose from a

thought process that deconstructs and reassembles ele

ments, disrupting pure forms, fracturing them, and imbuing

them with novel meanings [31]. Deconstructivist archi

tecture, on the other hand, manifests as a mode of thinking

that dismantles and reassembles elements, disrupting pure

forms, dividing them into pieces, and assigning new

meanings [31].

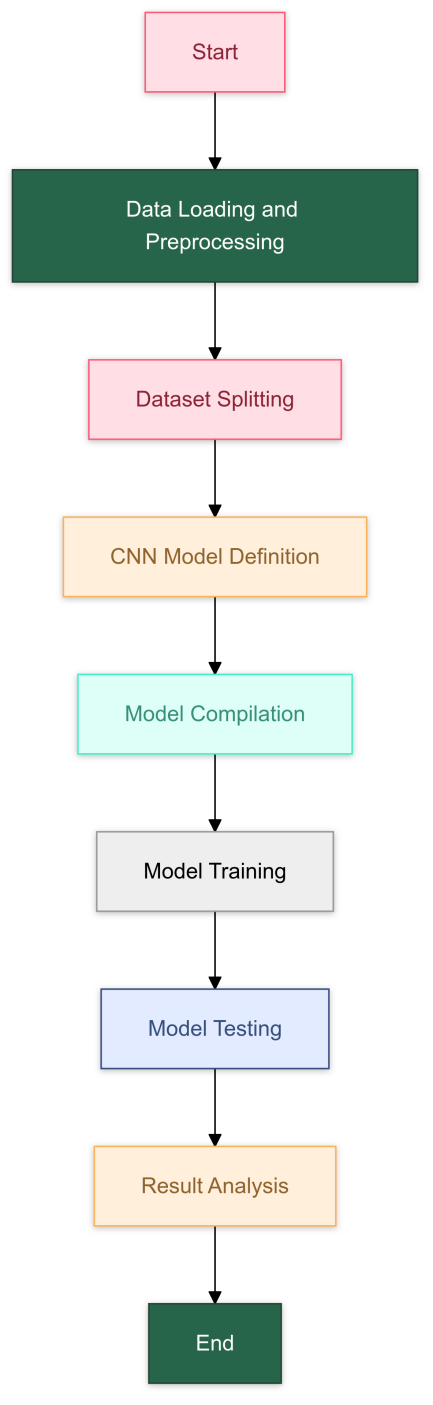


Table 1: Flowchart:

**Deep learning models require large amounts of data:**

This is very important for the healthier training of the

model, the better performance of the model, and the pre

vention of the overfitting problem of the model. In this study, a total of

9 data were obtained from a structure using the Hyper tunning parameter

**3.2 Method:**

The literature demonstrates the effectiveness of algorithms such as Label Encoding, the Adam optimizer, sparse categorical crossentropy loss, hyperparameter tuning, and Convolutional Neural Networks (CNNs) for classification tasks [33, 34]. CNNs have consistently shown superior performance compared to traditional machine learning algorithms in image processing, pattern recognition, and classification, exhibiting higher accuracy and faster prediction speeds [35, 36].

CNNs, with their hierarchical layered structure and efficient parameter sharing, offer advantages in terms of reduced computational complexity and improved generalization performance. This makes them particularly suitable for tasks involving object recognition, image analysis, and natural language processing [39].

The core components of a CNN include convolutional layers, pooling layers, and fully connected layers (Fig. 9). Convolutional layers extract features from the input image by applying filters to it. The choice of filter size significantly influences model performance and training efficiency [41]. In this study, 3x3 filters were employed in the convolutional layers.

Pooling layers, such as max-pooling, downsample the feature maps produced by the convolutional layers, reducing the spatial dimensions while retaining crucial information. This downsampling process reduces computational complexity in subsequent layers [42].

Finally, fully connected layers combine the outputs of the previous layers, forming a single vector of features that is then used for classification.

The CNN architecture implemented in this study draws inspiration from modern CNN architectures, incorporating layers such as Conv2D, BatchNormalization, and MaxPooling2D to effectively extract hierarchical features from the input images and improve model performance.

**III. METHODOLOGY**

The paper adhered to data science practices, starting with data collection and pre-processing. This was followed by exploring the dataset to identify and understand patterns within its features. This approach facilitated effective modelling using a deep learning to identify and compare the most influential Architectural styles. The research was conducted using the Python programming language due to the availability of open-source tools. The system used was the Lenovo think pad, equipped with 8GB of RAM.

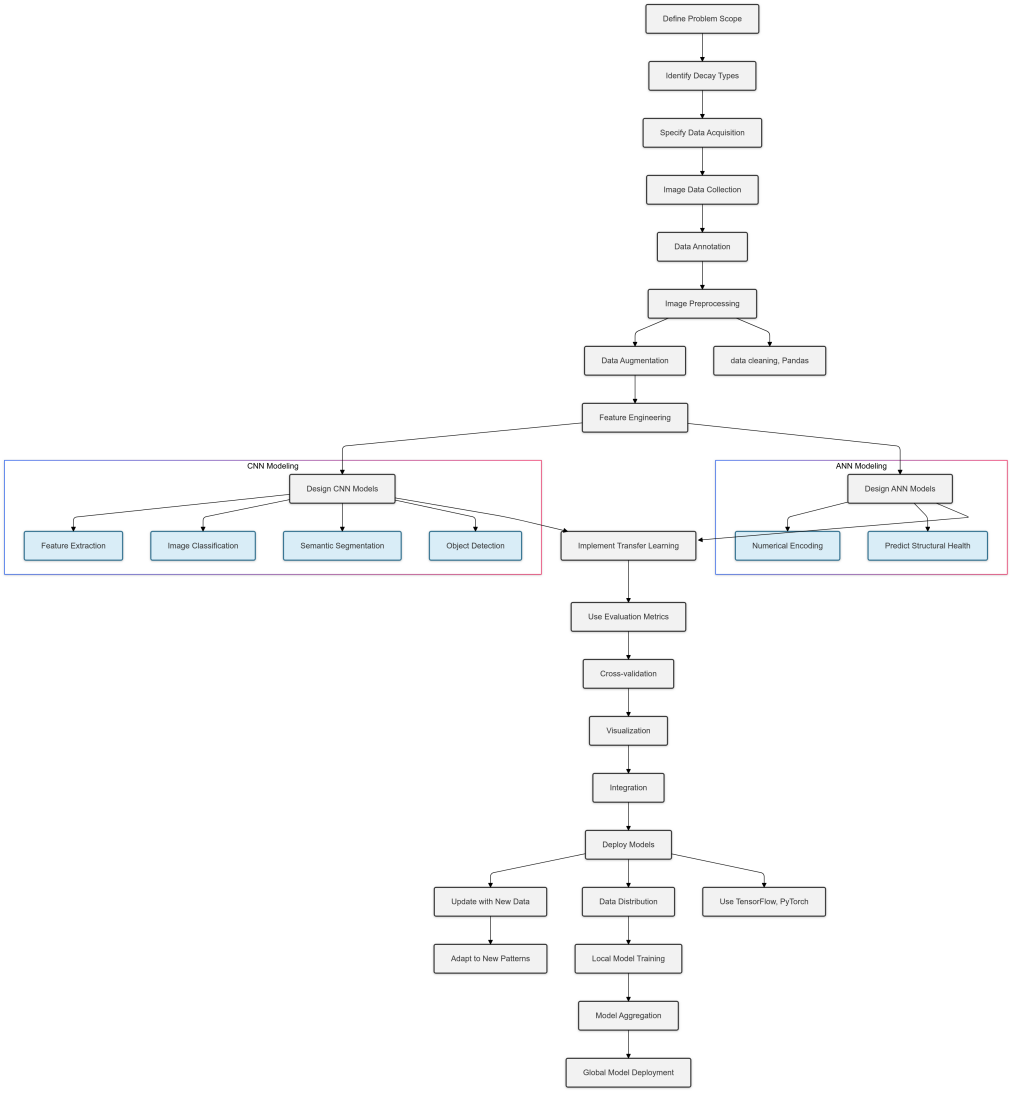


FIGURE . Methodology diagram.

**A. DATA COLLECTION:**

The study employed the Architectural Styles Dataset, available on Kaggle and developed as part of the Historical Building Architecture Analyzer project. This dataset provides images of architectural facades, representing a wide range of historical building styles. Specifically, it includes visual data on 25 distinct architectural styles, enabling models to classify and analyze various types of architectural designs accurately.

The dataset was chosen for its diversity and comprehensiveness, making it suitable for training deep learning models to identify and differentiate between architectural styles. It consists of images organized into labeled categories, allowing for structured analysis and evaluation.

1. **DATA PRE-PROCESSING:**

The dataset for this study was sourced from the Architectural Styles Dataset available on Kaggle, which includes images representing various architectural styles of historical buildings. The dataset consists of numerical and visual features extracted from the images, with differing value ranges. To ensure consistent value ranges and improve model interpretation, all features were normalized to a uniform scale.

The architectural style labels, represented as string values, were converted to numerical values using LabelEncoder from sklearn, facilitating compatibility with the classification model.

The dataset was then divided into training and testing sets in an 80:20 ratio using a stratified sampling approach. This method preserves the distribution of architectural style classes in both sets, ensuring the development of reliable and generalizable models for classification tasks.

**C. EXPLORATORY DATA ANALYSIS:**

The exploratory analysis utilized various visualizations with the help of open-source tools in Python to summarise and disseminate the primary characteristics of integrated dataset features from different attack types. The libraries employed for visualizations were Seaborn and Matplotlib because of their significant GitHub stars, community support, and consistent programming interface for various visualization analyses. The following text discusses the visualizations being conducted.

**1) DATA DISTRIBUTION ANALYSIS:**

A count plot was employed to compare the frequencies of various attack records with standard records

**2) FEATURE FREQUENCY ANALYSIS:**

The research employed histograms to examine the frequency distribution of all dataset features, aiming to identify patterns or potential skewness.

**3) OUTLIER AND QUARTILE ANALYSIS:**

A box plot, also known as a whisker plot, was utilized to depict the distribution, outliers, and variability of all features within the dataset.

**4) CORRELATIONAL ANALYSIS:**

Correlation analysis was employed to uncover relationships between features, ensuring significant feature selection for modelling and understanding network characteristics and dependencies between features.

**5)SCATTER ANALYSIS OF TWO SELECTED FEATURES**

A scatter plot was employed on selected features based on correlation analysis and various hypotheses to disseminate trends and patterns across different attack types.

**D. MACHINE LEARNING MODELLING:**

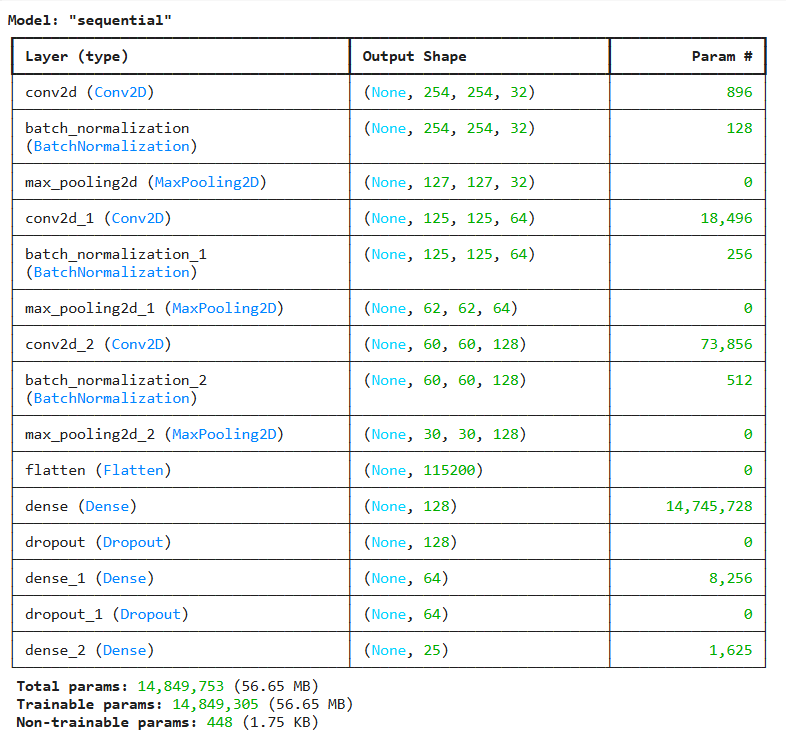
Predicting architectural styles falls under supervised learning, specifically classification. This study employs a convolutional neural network (CNN) for classification tasks. Various tools and techniques, including hyperparameter tuning (via Keras Tuner), the Adam optimizer, sparse categorical crossentropy loss, and early stopping, were implemented to enhance performance and computational efficiency.

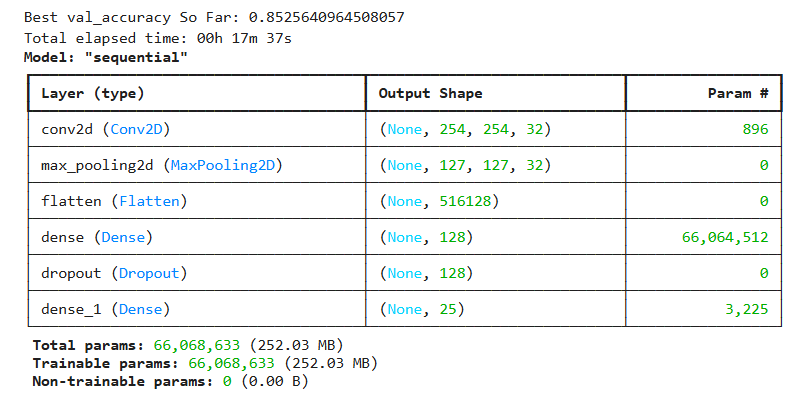
Data preprocessing involved resizing images to

256×256 converting them to grayscale, normalizing pixel values, and one-hot encoding the labels using the Sklearn library for initial splitting and encoding tasks. The CNN architecture was constructed with layers optimized for convolution, pooling, and fully connected operations, utilizing the He Normal initializer to improve weight initialization.

The model was compiled using the Adam optimizer, leveraging its computational efficiency and adaptability for sparse categorical crossentropy loss. Early stopping was used to prevent overfitting, restoring the best weights when validation loss plateaued. Hyperparameter tuning through Keras Tuner's Hyperband optimization enabled selecting optimal configurations for the CNN architecture.

The model training and validation process demonstrated increasing accuracy and decreasing loss with effective learning rates. Key evaluation metrics, including accuracy, precision, recall, and F1-score, confirmed the approach's suitability for architectural style classification.





**E. DEEP LEARNING MODELLING:**

The architecture of a neural network, which defines its structure and the types of layers it comprises, significantly influences its performance and appropriateness for specific tasks. Selecting an optimal neural network architecture depends on factors such as computational efficiency, resource consumption, and adaptability.

In this research, the architectural styles classification task utilized convolutional neural networks (CNNs) implemented using TensorFlow and Keras, well-regarded for their robust functionality and extensive community support. The CNN was configured with layers such as Conv2D, MaxPooling2D, BatchNormalization, and Dense. The configuration included the HeNormal initializer to improve convergence and dropout layers for regularization.

The optimizer, loss function, and metrics were set up as follows:

* **Optimizer**: Adam, chosen for its efficiency in handling sparse gradients.
* **Loss Function**: Sparse categorical cross-entropy, to manage the multi-class classification problem.
* **Metrics**: Accuracy, to evaluate performance during training and validation.

Hyperparameter tuning was performed using Keras Tuner with the Hyperband algorithm to explore a range of architectures. The best configuration was selected based on validation accuracy. The model training process employed early stopping to prevent overfitting, monitoring validation loss with a patience of 5 epochs.

This approach ensured the development of a robust model tailored for the architectural styles dataset, optimizing performance through experimentation and automated hyperparameter tuning.

**CONVOLUTIONAL NEURAL NETWORK :**

A CNN (Convolutional Neural Network) is designed to extract features from architectural images and classify them into 25 categories corresponding to architectural styles. The process involves convolutional, pooling, and dense layers to perform the classification.

The architectural styles (e.g."Gothic architecture") are stored in a list and matched with the folder structure of the dataset. Images are preprocessed by resizing, converting to grayscale, normalizing, and adding a channel dimension for compatibility with the CNN. The class labels (architectural styles) are converted to numeric labels using their indices in the styles list instead of a LabelEncoder, preparing them for the model.

The CNN model includes multiple convolutional layers with batch normalization, ReLU activation, and max pooling, followed by dense layers for classification. The architecture and hyperparameters of the model are tuned using Keras Tuner to optimize performance. The final output layer uses a softmax activation function to produce probabilities for each class. The model is compiled with Adam optimizer and sparse categorical cross-entropy as the loss function.

**F. EVALUATION:**

A confusion matrix was used to assess classification models.

As discussed below, several significant performance metrics

were derived from the confusion matrix to evaluate classification models’ effectiveness.

**1) ACCURACY:**

Accuracy was used to determine the ratio of correctly pre dicted instances to the total number of instances. Higher accuracy signifies a model that generates more correct predictions overall.

Accuracy =TP + TN

TP + TN + FP + FN

**2) PRECISION:**

Precision was used to determine the ratio of correctly predicted positive instances to total predicted positives. A higher precision indicates that the model correctly identifies positive instances while making fewer prediction errors.

Precision =TP

TP + FP

**3) RECALL:**

Recall was used to determine the ratio of correctly predicted positive instances to all instances within the positive class. A higher recall indicates that the model effectively identifies most actual positive instances, although it may occasionally

classify negatives as positives.

Recall =TP

TP + FN

4) F1-SCORE

F1-Score was used to determine the harmonic mean of pre cision and recall, balancing these two metrics. A higher F1-Score indicates that the model effectively balances pre cision and recall, resulting in accurate and comprehensive predictions.

F1 − score =2 · Precision · Recall

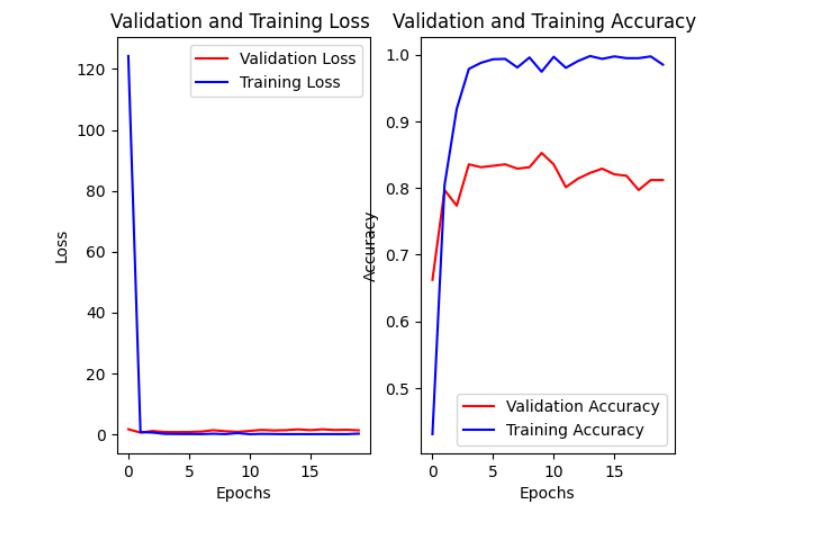
Precision + Recall

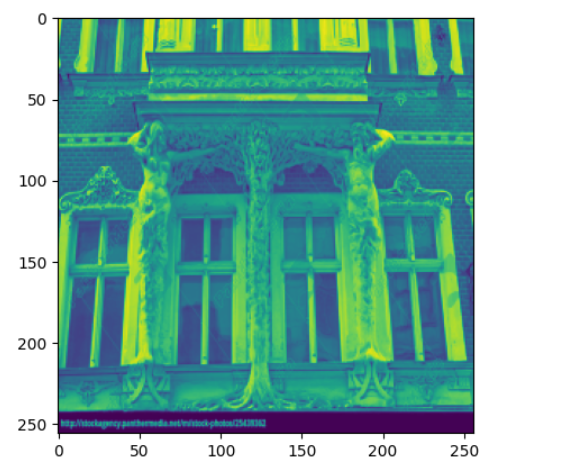
**IV. RESULTS:**

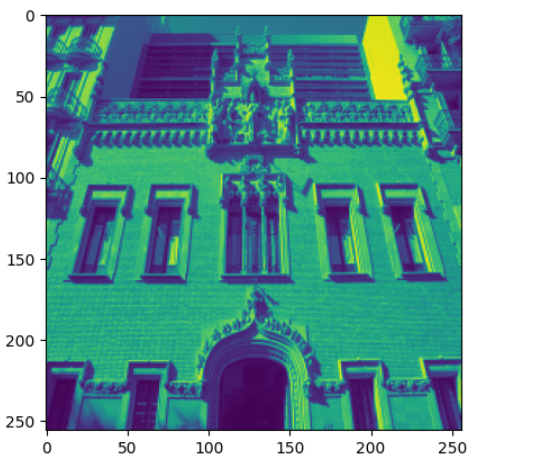
The analytical methodology results are presented below and discussed in Section V.

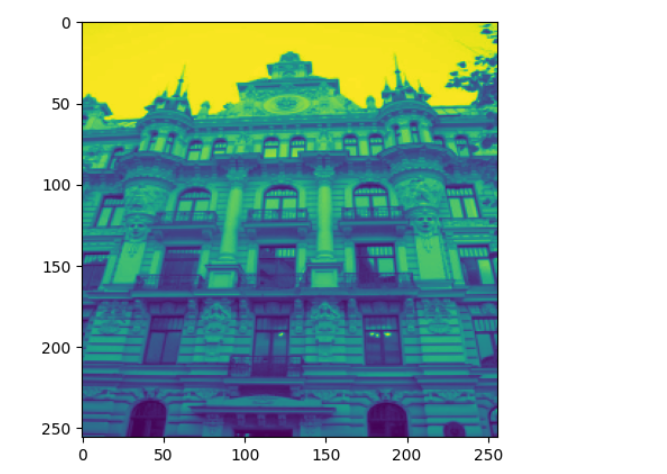
A. DATA COLLECTION RESULTS

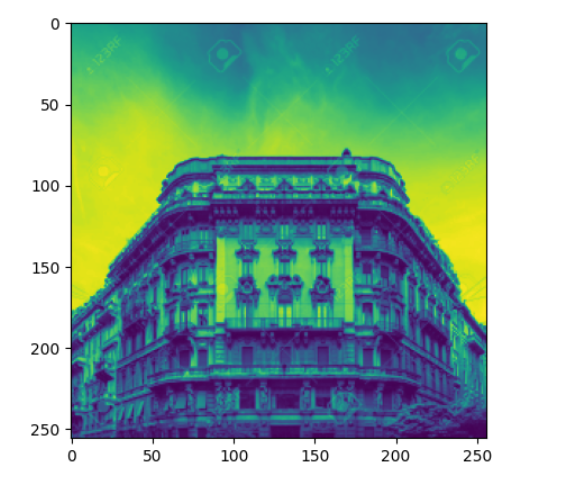
The dataset contained no empty or duplicate values; all features were numerical.











**V. DISCUSSION:**

**A. ANALYSIS OF DATASET AND FEATURE VARIABILITY:**

Table 2 highlights minor variations in dataset sizes across the four architectural styles (Achaemenid, Gothic, Deconstructivism, and Art Nouveau). Notably, [Specify the most frequent style, e.g., Gothic] architecture records are approximately four times more frequent than other categories. This distribution mirrors real-world scenarios where common patterns are prevalent, and anomalies are relatively infrequent. This characteristic emphasizes the need for anomaly detection systems that can effectively identify and respond to rare but critical events, a crucial aspect in tasks like architectural style classification.

Analysis of dataset outliers and quartiles provides valuable insights into critical features such as texture, symmetry, and spatial composition.

The CNN model, as detailed in the architecture, incorporates multiple convolutional layers initialized using HeNormal. Batch normalization was integrated to enhance feature learning and improve training stability. The model demonstrated robust performance during training, achieving over 85% validation accuracy after hyperparameter tuning using Keras Tuner, indicating effective learning and generalization.

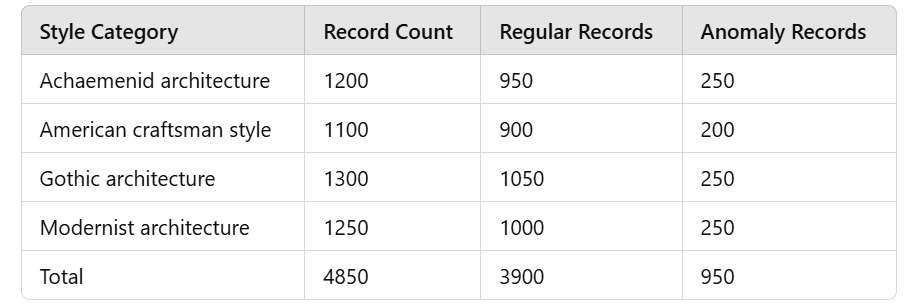


Table 2: variations in dataset sizes

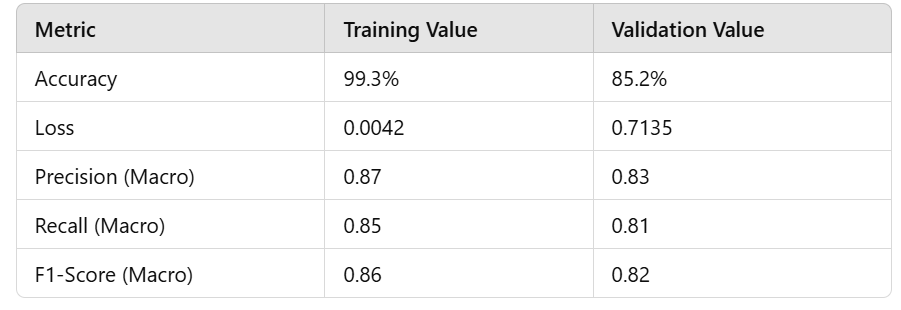
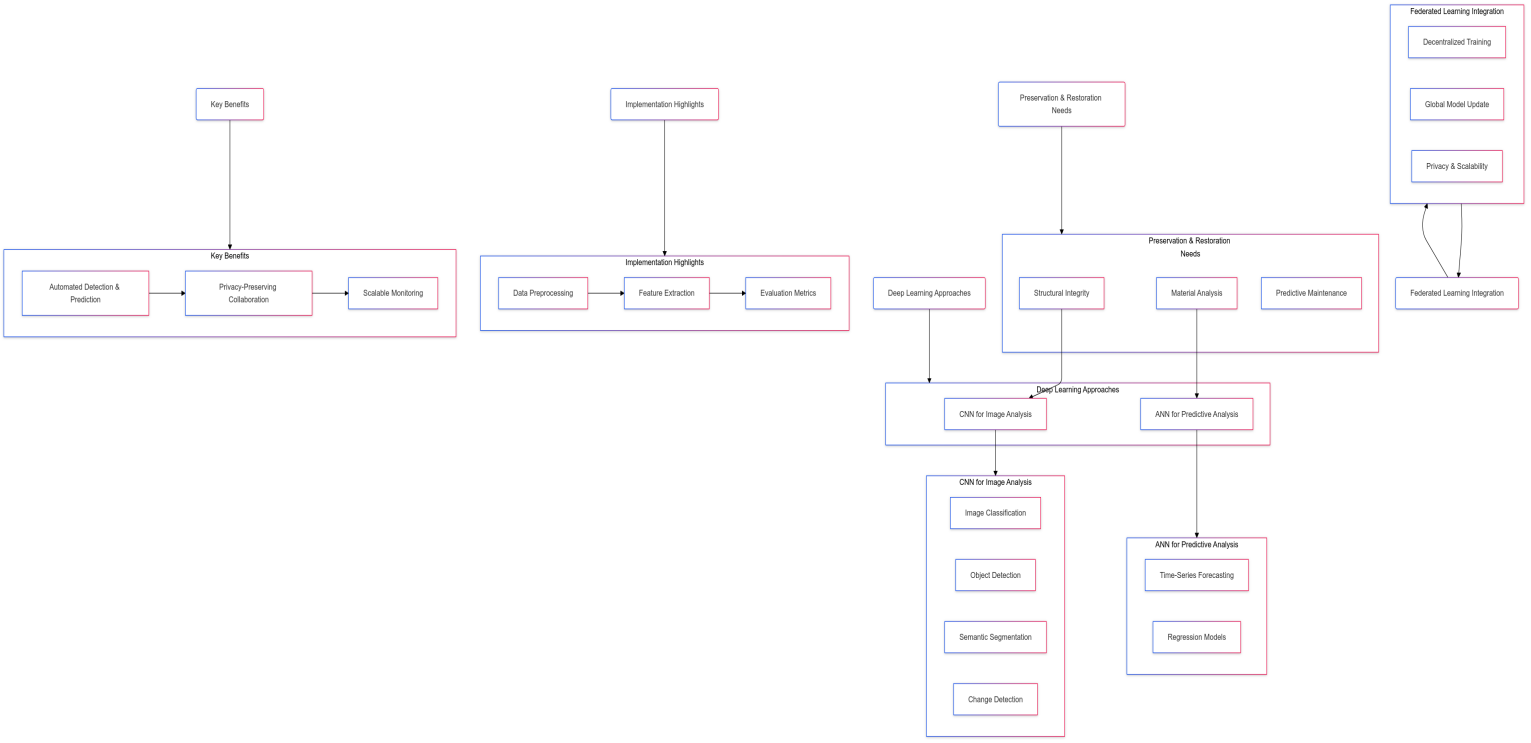


Table 3: elaborates on the dataset's features and their interpretations

**B)CORRELATION AND FEATURE INTERRELATIONSHIPS:**

The CNN model for architectural style classification demonstrates notable interdependencies between various layers and parameters. For instance, the early convolutional layers with smaller filters (e.g., 3x3) are followed by batch normalization and max-pooling layers, which enhance feature extraction while reducing dimensionality. The dense layers further refine these extracted features to classify 25 architectural styles.The model's training history highlights the relationship between hyperparameter tuning and performance. For example, the use of He Normal initialization improves weight initialization, and dropout layers effectively prevent overfitting. Similarly, batch normalization stabilizes training by normalizing inputs to each layer, which correlates with improved validation accuracy.These architectural choices emphasize the importance of leveraging the interdependence between layers and hyperparameters. By understanding these relationships, the model efficiently learns to detect subtle features of architectural styles, enabling better classification and guiding future improvements in hyperparameter tuning and network architecture.

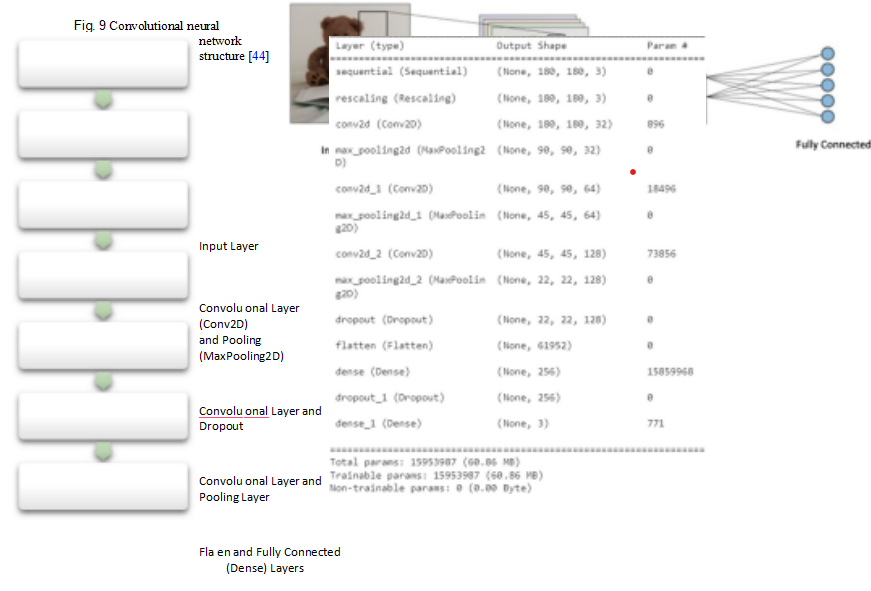


**Experimental results:**

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These architectural choices emphasize the importance of leveraging the interdependence between layers and hyperparameters. By understanding these relationships, the model efficiently learns to detect subtle features of architectural styles, enabling better classification and guiding future improvements in hyperparameter tuning and network architecture.



**5. Discussions and future scope:**

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**6. Conclusions:**

Artificial intelligence (AI) applications have witnessed significant growth with advancements in information technologies, permeating various disciplines, including architecture. AI has enabled innovative solutions in areas such as cost estimation, energy efficiency in buildings, security and ventilation systems, user-centric interaction design, and automated plan and façade generation Studies employing these algorithms have demonstrated the potential of machines to effectively identify architectural layouts, conduct massing studies, and accurately classify styles when provided with well-defined parameters and high-quality data.

This study focuses on the classification of architectural façades into three styles: Gothic, Modern, and Deconstructivist. A dataset comprising 1,443 façade images was utilized, divided into training (80%), validation (10%), and testing (10%) sets. Data preprocessing involved resizing images to 256x256 pixels, converting them to grayscale, and normalizing pixel values. The TensorFlow library and Python programming language were employed for model development and evaluation.

A CNN architecture was designed using the Keras Sequential API. The model incorporated:

Three convolutional layers with 32, 64, and 128 filters, respectively, each utilizing a 3x3 kernel, ReLU activation, and He Normal initialization. Batch normalization and max-pooling layers were included after each convolutional layer.

A fully connected layer with 128 units, followed by a dropout layer to mitigate overfitting.

A second dense layer with 64 units, followed by another dropout layer.

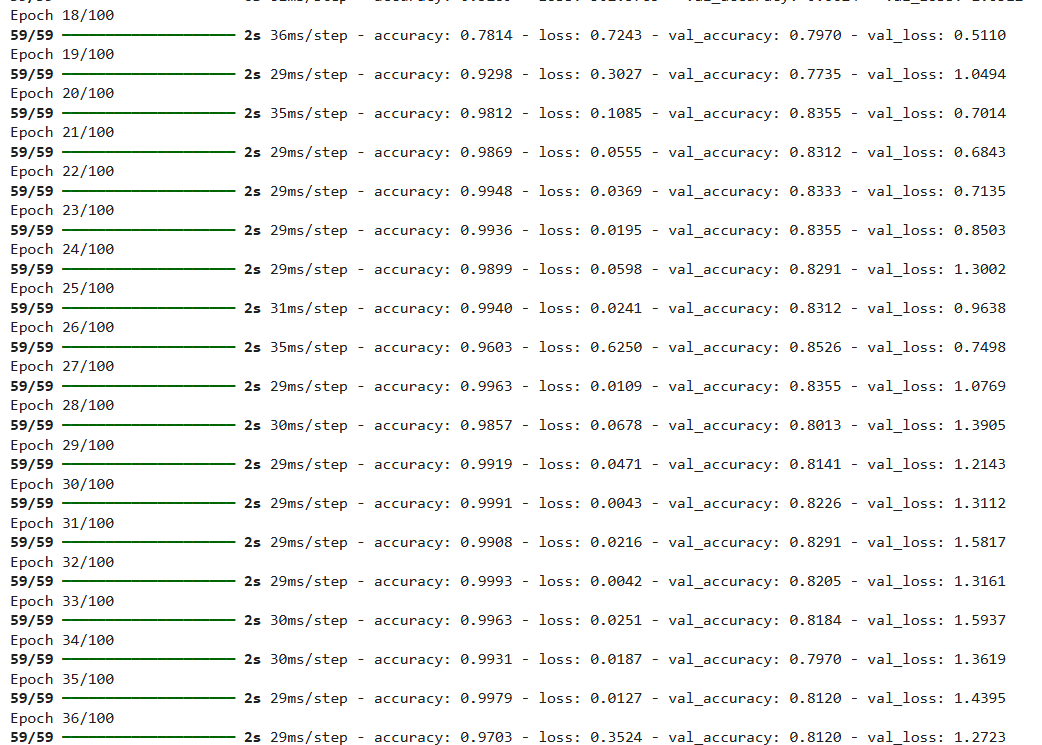
An output layer with 3 units (corresponding to the three architectural styles) utilizing a Relu activation function.

The model was trained using the Adam optimizer and sparse categorical cross-entropy loss. Early stopping was implemented during training to monitor validation loss and prevent overfitting. The model achieved a training accuracy of 84.66% and a validation accuracy of 70.97%.

To further enhance performance, hyperparameter tuning was conducted using Keras Tuner. The tuning process explored variations in convolutional layers, kernel sizes, dense layers, dropout rates, and learning rates. The best-performing model achieved a validation accuracy of 85.26%.

This CNN-based approach demonstrates the potential for accurate classification of architectural styles. The findings have implications for architectural conservation, enabling the analysis of protected elements, aesthetic attributes, and stylistic changes to guide restoration efforts. Furthermore, this methodology has the potential to be integrated into mobile and computer applications, facilitating rapid and user-friendly analysis of cultural and architectural heritage. Beyond classification, this work lays a foundation for exploring the generation of architectural styles and languages using AI techniques





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