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Ancient Buildings Identification Using Deep Learning Algorithm and Similarity Distance

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Abstract: Several cities in Indonesia such as Bandung, Cirebon and Bogor have many ancient buildings remaining, especially since the Dutch colonial period. However, identifying ancient buildings is a problem because people need to understand the existence of ancient buildings. A technology is needed to support the identification of ancient buildings, including their characteristics. The technology used is Artificial Intelligent which focuses on image processing and pattern recognition. This recognition process consists of Preprocess, Feature Extraction, and Building Image Classification. The Gaussian Blur method was used for the preprocessing, Sharpening used the Convolutional Kernel (SuCK) and Contrast Limited adaptive histogram equalization (CLAHE). All preprocessing is used to support feature extraction and image retrieval processes. This experiment uses several CNN models that perform feature extraction while the retrieval process uses Euclidean and Manhattan distances. Based on the results of the highest accuracy experiment used the DenseNet 121 model, where Initial process used Gaussian Blur, and the similarity distance with the Euclidean distance is 88.96% and 88.46% with the Manhattan Distance. For the initial process used SuCK method and the similarity with the Euclidean Distance is 88.26% and 87.81% with the Manhattan Distance. For the initial process used CLAHE and the similarity distance with the Euclidean Distance is 87.68% and 87.61% with the Manhattan Distance This research can be continued to identify ancient buildings with more complex characteristics and models.

Keywords: *ancient buildings, SuCK, CLAHE, DenseNet121, Gaussian Blur, Euclidean Distance, Manhattan Distence*

1. Introduction

This In West Java cities such as Cirebon, Bogor, and Bandung have several ancient buildings which are the legacy of the Dutch East Indies. Therefore, if someone visits the Old City Area or the Cultural Heritage area in Cirebon, Bandung, or Bogor. There are many ancient buildings both relics of the Dutch East Indies and Ancient Buildings category. The Dutch East Indies relics period are included in the category of cultural heritage and called Cultural Heritage Buildings [1]. Cultural heritage is the preservation of people's lives and livelihoods is protected by law from the danger of extinction. Ancient heritage can be divided into objects, buildings, structures, sites, and areas on land or in water that need to be preserved because they have essential values for history, science and education, religion, and culture, through the determination process [2]. The Cultural Conservation area is a geographical space unit with two or more Cultural Conservation sites located close together and showing distinctive spatial characteristics. While the Regional Museum is an institution that protects, develops, utilizes the collection, and communicates it to the public in the City Region. For this reason, the granting of Cultural Conservation status to Objects, Buildings, Structures, Locations, or geographic space units is carried out by the Regional Government based on the recommendation of the Cultural Conservation Expert Team [3].

In general, cultural heritage is a cultural wealth as a form of thought and behavior of human life, so it must be preserved and managed appropriately in the context of the welfare of the people of Bandung [4]. However, problems are discussed when it is uninformative and needs more strategic placement of how to find and sign systems containing information, history, and profiles of Ancient Buildings. Many visitors still need help finding information and navigating places in Kota Tua [5]. In conservation, development efforts are defined as increasing the potential value, information, and promotion of cultural heritage and its utilization through research, revitalization, and adaptation [6]. This research could find several ancient buildings, including their characteristics which used Artificial Intelligent technology. In addition, this research would also reveal the complete re-discovery of ancient buildings in one area, such as Bogor, Bandung, and Cirebon. Historical sites are a form of heritage and cultural heritage of ancestors that have value as a source of inspiration for the nation's life today and in the future [7]. This study also focused on introducing the inside of the Ancient Building. The building is a physical form of construction work that is integrated with its domicile, most of which are above or in the ground or air, which functions as a place for humans to carry out their activities, either for housing or residence, religious activities, religious activities, or religious activities—social, cultural, and special activities [8]. Our goal of this research is to carry them easier for Indonesian or international tourists to recognize ancient buildings, which are Indonesian cultural heritage that needs to be preserved.

2. Introduction

The object detection process is currently an important research area in the field of computer vision and computer vision artificial intelligence. One of them was detecting and recognizing buildings [9]. In recent years, some research papers had been published using

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machine learning and computer vision approach in ancient architecture and archaeology [10]. The other experiment for the application aspect, where the tour guide is not available this application will help the tourists to know the construction period or era by detecting the features of old spectacular architecture. Another study has focused on the constructional characteristics of old architectural sites using the Canny Edge Detector method [11]. The other proposes an idea to recognize and detect the textures, decorations, and other features of an ancient building based on machine vision. First, classify many surface textures images of ancient building components manually as a set of samples. Then, the convolution neural network is used to train the samples to get a classification detector. Finally, verify its precision [12] Another research about introducing Stone cultural heritage types based on weathering using Deep Learning and Artificial Neural Networks. The Stone cultural heritaged accuracy rates obtained from the DL and ANN models are 99.4% and 93.95%, respectively. The recall rate (96–100%) in each class of the DL model has been determined to be higher. Based on the results, the lowest precision rates in the testing phase were found in fresh rock (97%) and flaking (98%), while 100% precision rates were obtained in the other classification groups [14]. In historical buildings, surface cracks are essential indicators of potential structural damage. Natural disasters and indirect human factors, frequently encountered in recent periods, negatively affect historic buildings and structures. This proposes ReCRNet, a deep-learning architecture designed for classifying images of cracks [15].

In recent years, deep learning algorithms, and intense convolutional neural networks (CNNs) architecture, have been widely utilized as a reliable approach to studying classification characteristic features direct from original medical images or others [16,17]. In contrast to the Machine learning approach that relies on explicitly classified features, deep CNNs are a class of deep neural networks that can study high-dimensional features to maximize the network's ability to distinguish abnormalities between images [18]. Many CNN architectures have been designed for image classification and recognition. Each of these architectures differs in certain aspects, including the number and size of layers, the connections between these layers, and the overall network depth [19]. Because different network architectures are best suited for different problems, and it is hard to know In advance which architecture is the right choice for a particular task, empirical checks are often made recognized as the best way to make this decision [20].

3. Research Method

This research focused on 183 images of historical buildings from 3 different cities in Indonesia. So that the variations of historical buildings in this research are feasible, this research also does not focus on color characteristics. Therefore, all images must be preprocessed to reduce noise or increase the uniqueness of the image. There are three methods of image processing in this experiment: Blur, CLAHE, and SUCK. Gaussian blur works by blurring the image to reduce the noise. Next, CLAHE stands for Contrast Limited Adaptive Histogram Equalization, which equalizes the value of the image by reducing the contrast amplification. Last, SUCK, which stands for Sharpening Using Custom Kernel, is the opposite of the other two. SuCK sharpens the image to give the image more characteristics. However, the possible downside is that image noise might be worse when compared to the other two.

Image features will be extracted with several CNN models, namely InceptionV3, InceptionResNetV2, ResNet50V2, VGG19, and DenseNet201 [17]. These models have the same essential three CNN layers: convolutional, pooling, and fully connected. The difference between these CNN models is the architecture that builds the model. With such variations of CNN architecture, there is the possibility of a difference in output value from each CNN. Therefore, these CNN models are one of the factors that could affect the experiment. The extracted features will be compared with two distance metrics: Manhattan Distance and Euclidean Distance. Therefore, in research on building image retrieval, there are four main activities: collecting the images, preprocessing the images, feature extraction, and testing by finding the similarity between datasets. These primary activities should be carried out sequentially to obtain the maximum possible accuracy.

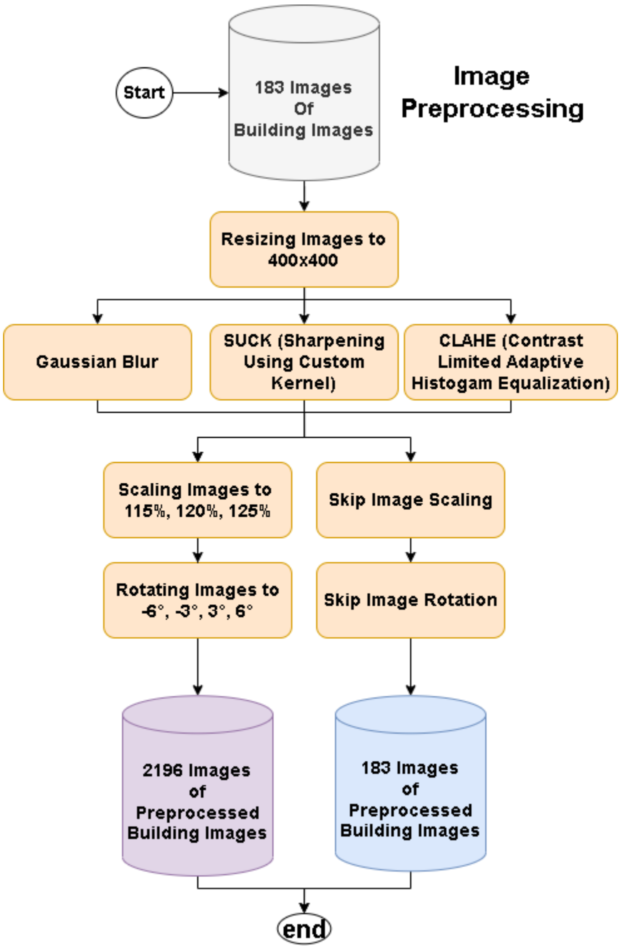
This research would find out more about the performance; the building dataset will be rotated and scaled, increasing the dataset and increasing the relative performance's validity. Thus, this research focuses on the performance comparison between these image processing methods, CNN Models, and Distance Metrics. A more thorough explanation can be seen in the following sections.

A. Collecting images of historical building

This experiment has three cities, each with about 17 to 24 historic buildings. Images were collected by visiting and taking pictures of the building or getting the image from the internet. Each image has different lighting, size, environment, or angle. These differences matter in the feature extraction. The point of image retrieval is to make the machine recognize similar images. As a result, it is required to preprocess the image to reduce noise, lighting, or any possible unnecessary difference in the image.

Fig 1. Example of Collected Images of Historical Building

Before preprocessing the images, they need to have a fixed formatted file name to make the process easier. These images are formatted into the unique naming format with three information combined without space but with an underscore symbol. Fig 1 shows the images of a historical building with the formatted file name.



As stated before, each image can have a difference in lighting and resolution size. For this experiment, it is required to have the same image size with a 1:1 ratio for the CNN to accept it as input. Hence, this process starts by turning the image into grayscale and resizing it to 400x400. Then, the image will be processed by one of the image processing methods. Next, there are two types of datasets: the building dataset (colored purple in Fig. 2.) and the testing/query dataset (colored blue in Fig. 2.). This process creates those datasets with the only difference in scale and rotation for the building dataset only. Finally, those datasets will be stored in different folders to differentiate between them. The procedure of image preprocessing is shown in Fig. 2.

B. Dataset setup

Fig 2. (a) Sample Of Blur Preprocessed Images (b) Sample Of "CLAHE" Preprocessed Images (c) Sample Of "SUCK" Preprocessed Images

Fig 3 informs the following experiment, consisting of images from three different cities: Bandung, Bogor, and Cirebon. Each city contains a different number of historical buildings. In this case, Bandung has 24 historical buildings, Bogor has 17 historical buildings, and Cirebon has 20 historic buildings. Each historical building contains three images at a similar angle. There are 72 images for Bandung, 51 for Bogor, and 60 for Cirebon. All these combined results in 183 images of historical buildings. The preprocessing process causes the amount of the image to increase for the building dataset. This process happens because of the rotation and scaling phase in the preprocessing. For the testing dataset, the amount is the same as before because of no rotation and scaling involved in the process. In the building dataset's case, the process turns images into 115%, 120%, and 125% in scaling percentage. There are three different scalings which cause the amount of building a dataset to increase to 549 images or nine images for each building. Then, the images get rotated into four variations of rotation which are -6°, -3°, 3°, and 6°. These rotation variations are chosen to differentiate from previously conducted studies by incorporating a minus-degree rotation. Therefore, 549 images multiplied by 4 equals 2196 images of the combined building dataset or 36 for each building.

C. Image Data Feature Extraction and Collection

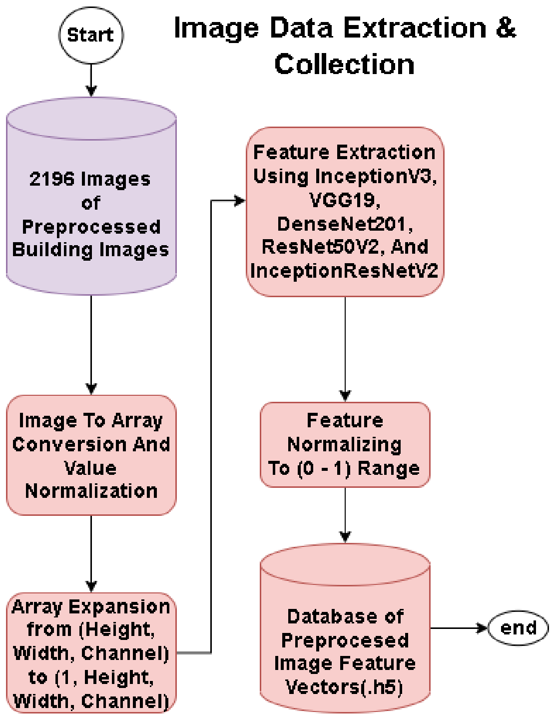


Fig 3. Data image collection and extraction Diagram

The diagram in Fig. 5 shows the process queries of every dataset in the testing to find 39 matching images. These 39 images are from 36 images from the building dataset and three images from the testing dataset to test the ability to recall itself. In the extraction phase, the query image undergoes the same phase depicted in green. The yellow color illustrates the result calculation phase. In the experiment, the distance between points in a straight line is known as Euclidean distance, whereas Manhattan distance is the sum of distances from all attributes [15]. Manhattan and Euclidean distances are used for measuring the similarity distance between images. After measuring the similarity of the image of the building, the next step is to display the results of sorting based on the name of the image, starting from the most similar and the least similar, totaling 39 images. Then the system will calculate the average percentage of similarity accuracy.

4. Result and Evaluation

After experimenting, the result for a testing query of CNN models with Euclidean Distance and Manhattan Distance is ready to be shown. The data will be analyzed to determine which CNN models are best suited for detecting historical buildings in three cities (Bandung, Bogor, and Cirebon) and supporting with Manhattan and Euclidean Methods.

A. Results

In this experiment, five different CNN models with Euclidean Distance are used in the testing query, and the same CNN models are used in a second test with Manhattan Distance. Regardless of whether a model uses the Manhattan Distance or the Euclidean Distance, the results show that all models have a high accuracy of picture retrieval. The first testing result will be shown the CNN model testing with Euclidean Distance. Fig. 6. Shows a complete detail of the total query above 70% between CNN models using the Euclidean Distance

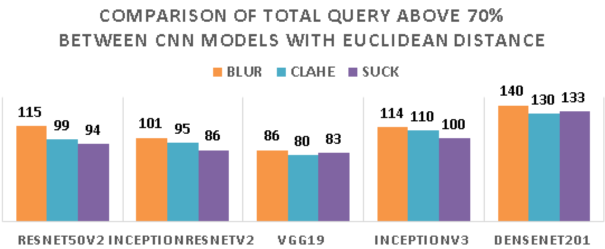


Fig 4. Comparison of Total Query Above 70% between CNN Models with Euclidean Distance

DenseNet201 is the CNN model with the highest number of images with above 70% retrieval accuracy, with 140 photos for the preprocess images blur, 130 images for the preprocess images CLAHE, and 133 images for the preprocess images SUCK. The other four CNN models were farther away than the DenseNet201 model. The InceptionV3 model came in second place because it had more than one hundred images for each of the three types of preprocessing images. While the CNN model with the lowest value is VGG19, there is no value in any of the three types of preprocess images that exceed one hundred images for the VGG19 model.

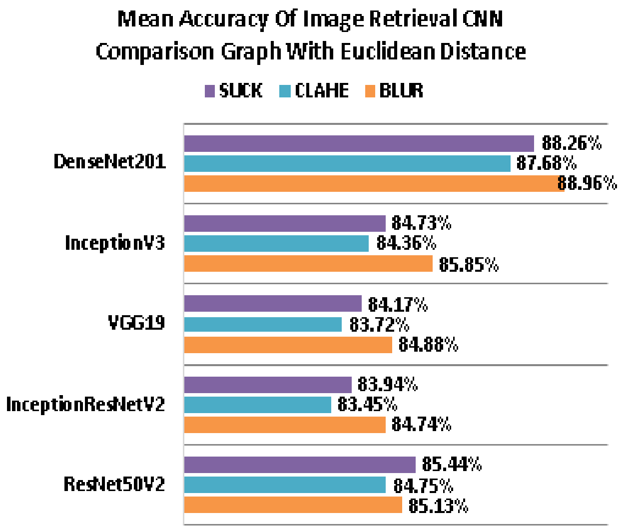


Fig 5. Mean Accuracy of Image Retrieval CNN Comparison Graph with Euclidean Distance

Fig. 7. shows the mean accuracy of image retrieval for each of the five CNN models with Euclidean Distance. Because of the three types of preprocessing images, each model has three types of mean accuracy data. The highest mean accuracy is DenseNet201, with 88.96% mean accuracy in the blur preprocess images. The lowest mean accuracy of image retrieval is the InceptionResNetV2 model when trying to detect the CLAHE preprocess images. DenseNet201 has a mean accuracy of 88.26% for SUCK preprocessing images and 87.68% for CLAHE preprocessing images. DenseNet201 has the highest overall mean accuracy for all types of preprocessing images.

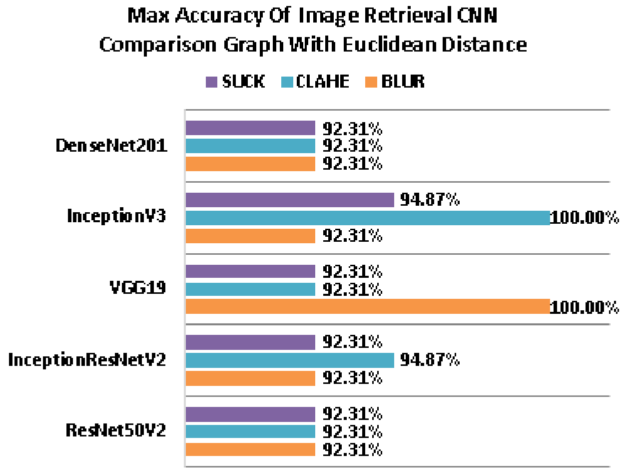


Fig 6. Max Accuracy of Image Retrieval CNN Comparison Graph with Euclidean Distance

While DenseNet201 has the highest overall mean accuracy for all preprocess image types, the highest accuracy that a CNN model gets when detecting three preprocessing images with Euclidean Distance is InceptionV3 for CLAHE preprocess image and VGG19 for blur preprocess image. Both CNN models have a 100% accuracy value for their respective preprocess image types, as shown in Fig. 8. Most models have the lowest max accuracy value of 92.31%.

The second test result is the CNN model testing with Manhattan Distance. The number of images with an accuracy value greater than 70% on the CNN testing model that uses the Manhattan distance is similar to that using the Euclidean distance. Fig. 9. shows the comparison of the total query above 70% accuracy from each CNN model.

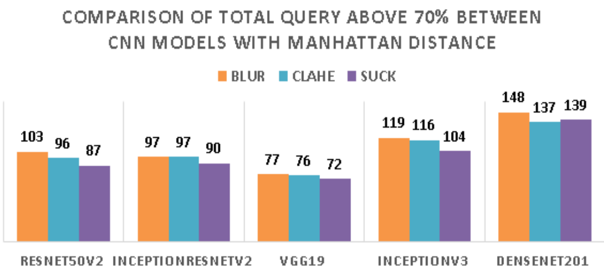


Fig 7. Comparison of Total Query Above 70% Between CNN Models with Manhattan Distance

The denseNet201 model has the highest number of images with an accuracy value above 70%. The DenseNet201 CNN model includes 148 images for blur preprocessing, 137 for CLAHE preprocessing, and 139 for SUCK preprocessing. The other four models produce results similar to those obtained using Euclidean Distance. The CNN model with the lowest number of total images is the VGG19, where the total number of images in each type of preprocessing image is below 80 images, as shown in Fig. 9.

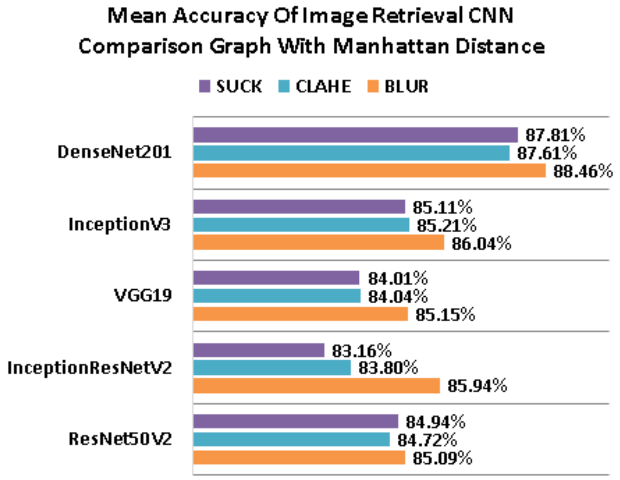


Fig 8. Mean Accuracy of Image Retrieval CNN Comparison Graph with Manhattan Distance

When this experiment was carried out, the different conditions for Each image resulted in a different accuracy value. Fig. 10 informs the mean image retrieval accuracy for each of the five CNN models with Manhattan Distance. Each model has three types of mean accuracy data due to the three types of preprocessing images. The highest mean accuracy is DenseNet201 with the blur preprocess images type, with an 88.46% mean accuracy. When attempting to detect SUCK preprocess images, the InceptionResNetV2 model has the lowest mean image retrieval accuracy. DenseNet201 has a mean accuracy of 87.81% for SUCK preprocessing images and 87.61% for CLAHE preprocessing images. Therefore, DenseNet201 has the highest overall mean accuracy for all types of preprocessing images with Manhattan Distance.

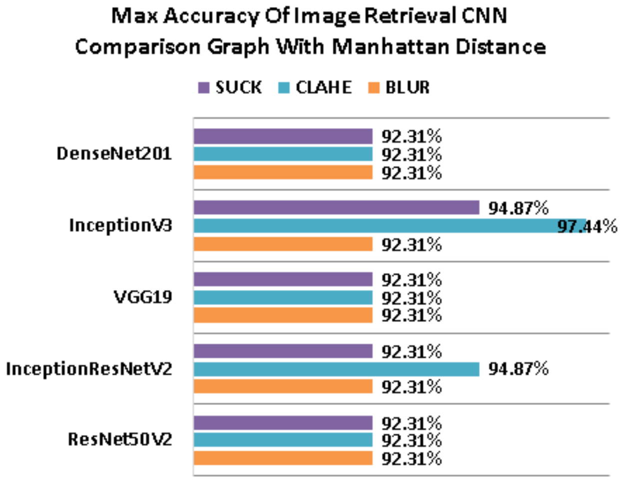


Fig 9. Max Accuracy of Image Retrieval CNN Comparison Graph with Manhattan Distance

Besides retrieving the mean accuracy for all CNN models in each preprocessed image type, the experiment also shows which CNN models reach the highest accuracy. The highest accuracy that a CNN model gets when detecting three types of preprocess images with Manhattan Distance is InceptionV3 for CLAHE preprocess images with a value of 97.44% accuracy. The second highest max accuracy value is InceptionV3 when detecting SUCK preprocess images and InceptionResNetV2 when detecting CLAHE images. Both models have a max accuracy value of 94.87%. The rest of the models have the lowest max accuracy value of 92.31%, as shown in Fig. 11.

B. Evaluation

The testing query resulted in a graph or table showing the mean accuracy of image retrieval CNN, the max accuracy of image retrieval CNN, the total of the query above 70% accuracy retrieval, and which historical building have the highest accuracy. The previously mentioned graphs are being used twice to show the testing result when using Euclidean Distance and another when using Manhattan Distance. The resulting data will determine which CNN model is the best practice for detecting historical buildings, either using Euclidean Distance or Manhattan Distance. Most of the model's mean accuracy of image retrieval CNN when using Euclidean Distance have a better result than when using Manhattan Distance. For example, ResNet50V2 and DenseNet201 have a better mean accuracy value on all preprocess image types when using Euclidean Distance than Manhattan Distance. InceptionV3 has a better result when using the Manhattan method.

In comparison, InceptionResNetV2 and VGG19 have a better result when detecting blur preprocess image type, and CLAHE preprocess image type using the Manhattan method but a better result when detecting SUCK preprocess image type using the Euclidean method. DenseNet201 has the highest mean accuracy value in all preprocess image types. DenseNet201 has a better result when using the Euclidean method. Table 1. shows a more detailed comparison of mean accuracy image retrieval using Euclidean Distance and Manhattan Distance.

COMPARISON OF MEAN ACCURACY IMAGE RETRIEVAL CNN MODELS USING EUCLIDEAN METHOD AND MANHATTAN METHOD

CNN Model	Euclidean Method			Manhattan Method		
	BLUR	CLAHE	SUCK	BLUR	CLAHE	SUCK
ResNet50V2	**85.13%**	**84.75%**	**85.44%**	**85.09%**	**84.72%**	**84.94%**
InceptionResNetV2	**84.74%**	**83.45%**	**83.94%**	**85.94%**	**83.80%**	**83.16%**
VGG19	**84.88%**	**83.72%**	**84.17%**	**85.15%**	**84.04%**	**84.01%**
InceptionV3	**85.85%**	**84.36%**	**84.73%**	**86.04%**	**85.21%**	**85.11%**
DenseNet201	**88.96%**	**87.68%**	**88.26%**	**88.46%**	**87.61%**	**87.81%**

The following testing query data is about the max accuracy of image retrieval CNN models data when using Euclidean Distance and Manhattan Distance. According to Table 2, most of the max accuracy between the Euclidean and Manhattan methods are the same, which has the color black, except for VGG19 when detecting blur preprocess image and InceptionV3 when detecting CLAHE preprocess image. The Euclidean method has a better result than the Manhattan method, which has a value of 100% max accuracy. At the same time, the Manhattan method has lower accuracy than when using the Euclidean method.

COMPARISON OF MAX ACCURACY IMAGE RETRIEVAL CNN MODELS USING EUCLIDEAN METHOD AND MANHATTAN METHOD

CNN Model	Euclidean Method			Manhattan Method		
	BLUR	CLAHE	SUCK	BLUR	CLAHE	SUCK
ResNet50V2	**92.31%**	**92.31%**	**92.31%**	**92.31%**	**92.31%**	**92.31%**
InceptionResNetV2	**92.31%**	**94.87%**	**92.31%**	**92.31%**	**94.87%**	**92.31%**
VGG19	**100.00%**	**92.31%**	**92.31%**	**92.31%**	**92.31%**	**92.31%**
InceptionV3	**92.31%**	**100.00%**	**94.87%**	**92.31%**	**97.44%**	**94.87%**
DenseNet201	**92.31%**	**92.31%**	**92.31%**	**92.31%**	**92.31%**	**92.31%**

The third testing query data is the highest number of total queries that exceed 70% accuracy in image retrieval. Table 3 shows that the DenseNet201 model with the Manhattan method has the highest number of total queries that exceed 70% accuracy in image retrieval, which is 148 images when detecting blur preprocess images. When using the Manhattan method, most CNN models have a better result. DenseNet201 has the highest overall number of total queries above 70% accuracy when detecting all preprocess image types. DenseNet201 excels in both the Euclidean and Manhattan methods compared to the other CNN models, while VGG19 has the lowest number of total queries above 70% accuracy in both methods.

COMPARISON OF TOTAL QUERY ABOVE 70% ACCURACY BETWEEN CNN MODELS USING EUCLIDEAN METHOD AND MANHATTAN METHOD

CNN Model	Euclidean Method			Manhattan Method		
	BLUR	CLAHE	SUCK	BLUR	CLAHE	SUCK
ResNet50V2	**115**	**99**	**94**	**103**	**96**	**87**
InceptionResNetV2	**101**	**95**	**86**	**97**	**97**	**90**
VGG19	**86**	**80**	**83**	**77**	**76**	**72**
InceptionV3	**114**	**110**	**100**	**119**	**116**	**104**
DenseNet201	**140**	**130**	**133**	**148**	**137**	**139**

The last data obtained during testing is which ancient buildings have the highest image retrieval accuracy. The ancient buildings with the highest image retrieval accuracy are from Bandung City. Whether the testing query uses the Euclidean or the Manhattan method, the historical buildings in the top ten highest accuracies are the historical buildings in Bandung City. The buildings from ranking one to ten have the same accuracy value. The test query results show that DenseNet201 is the most suitable CNN model to detect historical buildings. DenseNet201 has the highest image retrieval mean accuracy in all three preprocess image types, whether it uses Euclidean Distance or Manhattan Distance. DenseNet201 has the highest number of total queries that exceed 70% accuracy with Euclidean Distance and Manhattan Distance. But InceptionV3 has the highest max accuracy value in all the preprocess image types, especially when using the Euclidean method, which reaches 100% max accuracy when detecting CLAHE preprocess images.

Conclusion

This research is a breakthrough in recognizing and detecting ancient buildings in the Bandung, Bogor, and Cirebon areas using deep learning through several CNN models supported by retrieval methods, namely Euclidean and Manhattan Distance. In the recognition process of ancient buildings, an initial process is carried out so that the image is more straightforward, brighter, and free from image noise; the methods used are Gaussian Blur, SuCK, and CLAHE.

Based on the experiment, the highest average percentage of retrieval accuracy was carried out using the Blur method for preprocessing, the feature extraction process with the Densenet121 and Inception V3 models was supported by the retrieval process using the Euclidean method, namely 88.96% and 85.85%.

In future work, increasing the number of training samples could help improve the accuracy of detecting historical buildings. The increasing variety of angles and shape used to collect images of historical buildings may also aid the capability system in detecting and recognizing ancient buildings. In addition, more ancient buildings that the system could recognize would be beneficial.

Conflicts of Interest

The authors declare no conflicts of interest.

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Biographies

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