Title:

Utilizing Deep Learning to Categorize Buildings According to their Construction Year from Mobile Photographs.

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Level of study or work: Masters Studies (Thesis)
(Bachelor thesis, master, PhD, research, project, etc.)

Information about you (and your team): I was a master's Student that completed her program in the month of April in the department of Photogrammetry and Geoinformatics at Hochschule für Technik Stuttgart.

Area of interest

(Identifying the problem, explain why it is important and the current relevance of the topic, up to 250 words)

Studies have shown that the construction period or year is a critical factor in modeling the energy consumption of buildings. It serves as a proxy for key attributes such as thermal insulation, ventilation rate, and glazing ratios. Consequently, older buildings often consume more energy than newer ones due to less efficient construction standards and materials.

The age of the building is an important characteristic, because in each building era, common construction methods can be found, as well as typical component areas such as window sizes, building shape, number of floors, building size, all of which exert a substantial impact on the heating and consumption demand. The building age classes are based on historical incisions, the dates of statistical surveys, and changes in the thermo-technical properties over time.

Additionally, as per information provided by the Company I worked for, there are two key parameters involved in calculating energy demand and consumption of buildings: the construction year of the buildings (buildings age) and the energetic parameters of the buildings. However, for the purposes of this research, the emphasis was placed on predicting the construction year or age of the buildings.

This research presents a scalable deep learning methodology designed to accurately predict building age information across the various districts of Baden-Württemberg, Germany. The study covered eight districts, namely Leutenbach, Mundelsheim, Sindelfingen, Kirschheim, Kirschdorf, Allmendingen, Ebhausen, and Kornwestheim. The age of these buildings varied widely, spanning over 160 years, with construction dates ranging from 1859 to 2022.

Approach to the problem

(Describe your methodology or technology and how it will solve the problem you identified, up to 300 words)

This research aimed to employ machine learning techniques for estimating building ages within specified study areas and extending to regions beyond. The data collection and preparation process involved describing building images and corresponding construction years, including extensive data editing and labeling to ensure accuracy. The variables considered encompassed a diverse range of buildings within the study area, selected for their representation of various architectural styles, construction materials, and geographic locations. This diversity in the dataset was crucial for training a robust model capable of generalizing well to different building types and regions.

The research design involved training pre-trained Convolutional Neural Networks (CNNs) for image classification. Specifically, three CNN models were utilized and compared: VGG16, ResNet50, and EfficientNet, all of which are well-suited for mobile photographs. Additionally, transfer learning methods—feature extraction and fine-tuning—were employed and evaluated to determine the most effective approach for this research. The combination of these architectures and transfer learning techniques provided a thorough exploration of diverse methodologies.

These models were tasked with categorizing buildings into different construction year periods based on visual features extracted from the images. Concurrently, a regression model was developed to predict the actual construction years of buildings, providing a precise estimation rather than a categorical classification.

Evaluation metrics, including accuracy, precision, recall, and F1 score, were employed to assess the performance of the models. These metrics provided a comprehensive understanding of how well the models performed in various aspects, such as correctly identifying the construction year categories and minimizing false predictions.

The outcomes of this research have significant implications for urban planning, historical preservation, and real estate market analysis. By providing reliable estimates of building ages, the models developed in this study can assist local authorities and planners in making informed decisions regarding infrastructure maintenance, heritage conservation, and urban development projects.

Results, conclusions and next steps

(Present your results and conclusions of your study, up to 250 words)

This study highlighted the versatility of deep learning for image classification across diverse datasets. It highlights the importance of using appropriate pre-trained models, coupled with the right transfer learning methods and a sufficient volume of data, to achieve optimal results. The EfficientNet and ResNet50 models outperformed the VGG16 model, as the former utilized transfer learning by feature extraction while the latter used fine-tuning. A significant finding emerged when shifting from the fine-tuning transfer method to the feature extraction transfer learning method, showcasing the distinct impact of these techniques due to their unique characteristics.

The results obtained significantly address the research questions by successfully categorizing buildings based on their construction year. Despite the dataset's size limitation, each building image was assigned to a specific category within the four defined classes for this study. This study makes several important contributions to the research domain. Firstly, by predicting building ages, it provides a crucial parameter for assessments related to energy demand and consumption, thereby enhancing the precision of such analyses.

Moreover, the research offers new insights by advocating for the inclusion of mobile photographs in diverse datasets, especially those with spatial features or coordinates, thereby expanding the scope of data collection methods. Lastly, by addressing the gaps between two transfer learning methods and pre-trained models, the study provides valuable guidance for future researchers. It assists them in selecting the most appropriate approach based on dataset characteristics, size, and research objectives, contributing to the ongoing refinement of transfer learning techniques.

References

(Additional information, publications, or links, up to 200 words, optional)

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