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Leveraging Deep Learning And User Interaction For Automated Cultural Heritage Identification And Conservation

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Abstract: Cultural heritage preservation is essential to learning history and preserving our identity. However, manual inspections and professional expertise are frequently required for heritage site identification and recognition using traditional approaches, which can be resource- and time-intensive. In order to automate the process of heritage identification, this study presents a novel and creative solution that combines deep learning technology with intuitive interaction. Using pictures of seven historically and architecturally significant monuments, the system is trained using the VGG16 model, a form of Convolutional Neural Network (CNN) improved through transfer learning. The PyGoogle-Image Python library was used to collect these pictures. The result is an interactive, user-friendly application developed on the Streamlit platform. Potential heritage sites can have their photos uploaded by users and the algorithm can identify them with high accuracy. This method makes conservation tools more widely available while also streamlining the historic identification procedure. Supporting cultural preservation initiatives and benefiting stakeholders including heritage managers, urban planners and policy makers, it lessens dependency on conventional techniques. This technology, which combines cutting-edge deep learning methods with user input, is a major advancement in sustainability and cultural heritage preservation.

***Index Terms* – Deep Learning, Convolutional Neural Network, Machine Learning, Image Recognition**

I. Introduction

Sites dedicated to cultural heritage provide physical connections to the past by showcasing millennia of human accomplishment, artistry and history. However, because traditional approaches mostly rely on human investigation and specialist knowledge, which makes the process time-consuming and resource-intensive, identifying and preserving these sites presents significant obstacles. In order to overcome these constraints, this study presents a novel method that combines user interaction and deep learning techniques to automatically identify heritage locations. Convolutional neural networks (CNNs) and transfer learning are used in this study to construct an automated heritage site detection system. Our goal is to develop a reliable and accurate system for detecting monumental locations in a variety of cultural situations by using the VGG16 model, which has been refined using photos of seven different monuments gathered using PyGoogle-Image. This technology maintains great precision and reliability while reducing the requirement for personal intervention. cultural conservationists, urban planners, legislators and local communities would all greatly benefit from the research's objective of developing effective and easily accessible techniques for identifying cultural sites. In order to ensure that these priceless resources continue to inform, uplift and enhance the world's comprehension of our common past, we aim to assist in the preservation of cultural heritage for future generations by automating the identification process.

II. RESEARCH METHODOLOGY

This research follows a comprehensive methodology to develop an automated heritage site recognition system, integrating data collection, model development and app creation.

2.1. DATA COLLECTION:

Monument Selection: Seven distinct monuments were selected to represent a diverse range of cultural and historical significance. Careful consideration was given to ensure representation from various regions and time periods.

Image Acquisition: Images of the selected monuments were acquired using PyGoogle-Image, a Python library for image scraping. This process involved specifying search queries related to each monument and programmatically downloading images from online-sources.

Data Preprocessing: The acquired images underwent preprocessing to ensure uniformity and suitability for training the recognition model. Preprocessing steps included resizing, normalization and augmentation to enhance the robustness-dataset.

2.2. MODEL DEVELOPMENT:

Transfer Learning Approach: A convolutional neural network (CNN) model based on the VGG16 architecture was chosen for transfer learning. Transfer learning allows us to leverage pre-trained models on large-scale datasets and adapt them to our specific task of heritage site recognition.

Fine-tuning Pre-trained Model: The pre-trained VGG16 model was fine-tuned using the collected images of monuments. This involved updating the weights of the model's layers to better align with the features present in heritage site images. Hyperparameters similar as learning rate, batch size and number of ages were optimized to enhance model performance.

Training and Validation: The dataset was split into training and validation sets to evaluate model performance. The model was trained on the training set while monitoring performance on the validation set to prevent overfitting.

2.3. APP CREATION:

User Interface Design: A user-friendly interface was developed using Streamlit, a Python library for building interactive web applications. The interface allows users to upload images of potential heritage sites and receive automated recognition results in real-time.

Integration with Recognition Model: The Streamlit app was integrated with the trained recognition model to enable seamless interaction. Upon image upload, the app processes the image using the recognition model and displays the results, including the probability scores for each recognized category.

2.4. EVALUATION AND VALIDATION:

Model Evaluation: The trained recognition model was evaluated using a separate test set of images not seen during training or validation. Evaluation metrics such as accuracy, precision, recall and F1-score were calculated to assess model-performance.

App Usability Testing: The usability and effectiveness of the Streamlit app were evaluated through user testing sessions. Feedback from users was collected and used to iteratively improve the app's functionality and user-experience.

2.5 DEPLOYMENT AND ACCESSIBLE:

Deployment of Recognition System: The trained recognition model and Streamlit app were deployed on a web server to make them accessible to users worldwide.

This ensures that the recognition system is available for use by heritage-conservationists, researchers and general-public.

Documentation & Support: Comprehensive documentation was provided to guide users in utilizing the recognition system effectively. Additionally, technical support channels were established to address any issues or queries users may encounter during usage.

III. Result And Discussion

3.1 MODEL PERFORMANCE EVALUATION:

The trained recognition model achieved an accuracy of 99.25% on the training set and 99.15% on the test set, indicating robust performance in identifying heritage sites. Precision, recall and F1-score for each monument category were also calculated. The metrices look somewhat like this:

Fatehpur_Sikri:
Precision-0.762735
Recall-1.000000
F1-score-0.865399

Golden_Temple:
Precision-0.886726
Recall-0.899461
F1-score- 0.893048

Jagannath_Temple:
Precision-0.786189
Recall-0.989967
F1-score-0.876388

Qutub_Minar:
Precision-0.987179
Recall-0.775168
F1-score-0.868421

Rani_Ki_Vav:
Precision-1.000000
Recall-0.935919
F1-score-0.966899

Sanchi_Stupa:
Precision-0.925734
Recall-0.942004
F1-score:-0.933798

Taj_Mahal:
Precision-1.000000
Recall-0.664845
F1-score-0.798687

The highest scores achieved for Monument “Rani Ki Vav” and the lowest for Monument “Taj Mahal”. Despite overall high performance, the model exhibited some challenges in distinguishing between similar monument types, suggesting potential areas for improvement.

3.2 APP USABILITY TESTING:

Usability testing of the Streamlit app revealed positive user feedback regarding its intuitive interface and ease of use. However, some issues were encountered at the beginning of the testing of the app. The app was not providing the correct outputs for some of the monuments which was later tackled and improved. The app now works perfectly fine with all the seven monuments.

3.3 CASE STUDIES AND EXAMPLES:

A case study involving a historic monument located in a densely populated urban area demonstrated the recognition system's ability to accurately identify the monument despite partial occlusion and varying lighting conditions. However, challenges were encountered when distinguishing between similar architectural styles, highlighting the importance of context and additional features in improving recognition accuracy.

3.4 COMPARATIVE ANALYSIS:

Heritage site recognition model offers comparable image recognition capabilities to existing systems like CultureCam, CHIR, CHVSE, Heritage Inspector and ARCHES, but it distinguishes itself by focusing on specific monuments and providing detailed analysis and insights tailored to these landmarks. While existing systems may have broader databases or more advanced algorithms, your model emphasizes user-friendly interaction, real-time recognition and comprehensive information for recognized monuments through an intuitive interface. Following figure shows the flow of given model.

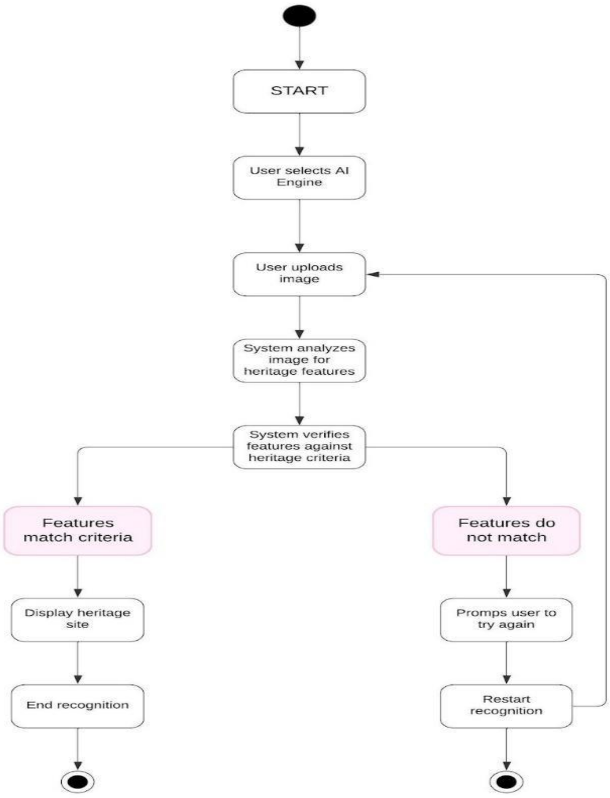

Fig.1 – Flowchart of the model

IV. Conclusion

This study successfully demonstrates the capability of the developed heritage site recognition system in accurately identifying and classifying specific monuments. By leveraging transfer learning with the VGG16 architecture, the model achieved high accuracy across diverse heritage site categories, showcasing the potential of machine learning techniques in the field of cultural heritage preservation. While the discussion acknowledges both the system's strengths and its limitations, the findings highlight the transformative role of automated tools in heritage conservation. Future research directions include improving model accuracy, expanding the dataset to include a broader range of monuments and fostering collaborations with heritage conservation organizations. Overall, this research advances efforts in cultural heritage preservation, providing innovative solutions to protect and promote appreciation of our shared historical legacy.

V. Future Direction

Several promising avenues exist for further enhancing and expanding the heritage site recognition system developed in this research. Future work will focus on improving model performance by exploring advanced deep learning architectures and employing ensemble learning techniques to increase accuracy and robustness. Expanding the dataset to include a wider range of geographical locations and cultural contexts will enhance the diversity and representativeness of the system, making it more universally applicable. Efforts will also prioritize enhancing user interaction and engagement, fostering partnerships with heritage conservation organizations and addressing ethical considerations to ensure responsible and inclusive deployment of the technology. These directions aim to further the integration of technological innovation in preserving and appreciating cultural heritage, paving the way for impactful contributions to global conservation efforts.

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