LANDMARK RECOGNITION USING CNN MODEL

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Abstract: *The increasing availability of digital images from tourists, travelers, and mapping platforms has created a demand for intelligent systems capable of automatically identifying famous landmarks. This paper presents a Landmark Recognition System that uses a Convolutional Neural Network (CNN) model to classify landmarks from user-uploaded images. The system leverages a pre-trained TensorFlow Hub model optimized for Asian landmarks and integrates a Streamlit web interface to provide real-time predictions and user interaction. Once an image is processed, the system identifies the landmark and retrieves its geographical details—including address, latitude, and longitude—through the Geopy library, displaying them interactively on a map. The proposed system achieves high prediction accuracy and offers an intuitive interface for end users. This work demonstrates how the integration of deep learning and geolocation technologies can enhance applications in tourism, navigation, and education.*

Keywords: **Convolutional Neural Network (CNN), Landmark Recognition, Deep Learning, TensorFlow Hub, Streamlit, Image Classification, Geolocation, Artificial Intelligence, Tourism Applications**

1. INTRODUCTION

Landmarks serve as important cultural, historical, and geographical markers that define the identity of regions and attract global interest. With the exponential growth of digital imagery—particularly through social media, travel platforms, and mapping services—there is a rising demand for automated landmark recognition systems. Manual identification of landmarks from such massive image datasets is time-consuming and prone to errors. Therefore, developing intelligent systems that can recognize landmarks automatically has become crucial for applications in tourism, navigation, cultural preservation, and geographic information systems.

In recent years, several approaches have been proposed to address this problem. Early methods relied on traditional computer vision techniques such as Scale Invariant Feature Transform (SIFT) and Speeded-Up Robust Features (SURF) to extract and match features between images. However, these methods required extensive manual feature engineering and performed poorly under varying lighting conditions, viewing angles, and partial occlusions. Subsequent studies began exploring machine learning techniques and geotagged datasets for image-based localization.

For instance, Heys and Efros (2008) attempted geographic information estimation using nearest neighbour searches, while Weyand et al. (2016) introduced PlaNet, a CNN-based model trained on millions of geotagged images to predict photo locations. Although these models marked major progress, they often required massive computational resources, large datasets, and lacked real-time performance.

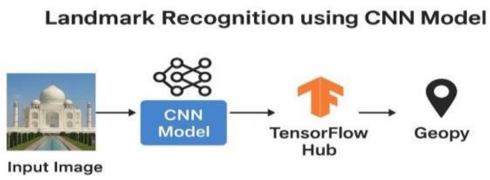

Figure 1.Landmark Recognition System

Figure 1 illustrates the workflow for landmark recognition using a CNN model. In this process, an input image (such as the picture of the Taj Mahal) is first processed by a CNN (Convolutional Neural Network) model to extract features and recognize the landmark. The recognized data is then passed through TensorFlow Hub, which is a platform for reusable machine learning modules. Lastly, the identified landmark information can be geo-referenced using Geopy, linking the recognition result to a specific geographic location. This pipeline demonstrates a typical approach for automating landmark detection and geolocation using deep learning tools and APIs.

A major benefit of using CNN-based approaches for landmark recognition is their ability to learn complex and distinct features from images, even when landmarks have varying architectural styles or partial occlusions. By leveraging pre-trained models and advanced feature extraction techniques, the neural network can classify images from a diverse set of global landmarks with high accuracy. Integration with tools like TensorFlow Hub allows for modularity and scalability in deploying these models, while geographic mapping via tools such as Geopy enables applications in tourism, smart photography, and automated tagging of images when metadata is missing.

To overcome these limitations, the proposed system introduces a Landmark Recognition Model using Convolutional Neural Networks (CNNs). This system leverages TensorFlow Hub to integrate pre-trained CNN models optimized for landmark identification, enabling real-time predictions from user-uploaded images. The system further incorporates Geopy to fetch the geographical coordinates and address of the recognized landmarks, and displays them interactively using Streamlit. This approach provides a comprehensive and user-friendly solution that bridges image recognition with geolocation visualization, outperforming traditional methods in both accuracy and usability.

2. BACKGROUND MATERIAL

The advancement of **Artificial Intelligence (AI)** and **Deep Learning (DL)** has revolutionized computer vision applications such as image recognition, object detection, and classification. Among these, **landmark recognition** is an emerging research area that aims to identify famous monuments, buildings, or natural structures from digital images. Traditionally, image recognition depended on manual feature extraction methods, which required domain expertise and extensive computation. However, the emergence of **Convolutional Neural Networks (CNNs)** and **transfer learning** has enabled the automatic extraction of meaningful features from large-scale image datasets, improving accuracy and efficiency.

The **Landmark Recognition Using CNN Model** leverages these advancements to build an intelligent and automated system capable of identifying landmarks and retrieving their geographic details. The background material of this project discusses the key theoretical concepts, technologies, and previous methodologies that form the foundation for the proposed system. Recent years have witnessed remarkable progress in **image recognition** and **deep learning**, leading to efficient methods for **automated landmark recognition**. This chapter reviews the fundamental background material, existing research, and recent developments relevant to the **Landmark Recognition Using CNN Model**. It explains how deep learning architectures, benchmark datasets, and modern frameworks form the foundation of this project.

2.1 Image Recognition and Computer Vision

Image recognition is the process of identifying and classifying objects or scenes within an image. It forms the core of computer vision systems that allow machines to —see|| and interpret visual information.

2.1.1 Evolution of Image Recognition

Early image recognition relied on manually engineered feature extraction techniques, including Scale Invariant Feature Transform (SIFT), Speeded-Up Robust Features (SURF), Histogram of Oriented Gradients (HOG), and Oriented FAST and Rotated BRIEF (ORB). While effective for small datasets, these methods struggled with real-world variations such as lighting, viewpoint, and background clutter, limiting scalability.

2.1.2 Limitations of Traditional Approaches

Traditional methods required expert knowledge for feature design, were not adaptable to new datasets, and were computationally inefficient for large-scale image collections. These limitations motivated the adoption of deep learning-based systems that automatically learn discriminative features.

2.2 Deep Learning and Convolutional Neural Networks (CNNs)

Deep learning (DL), a subfield of AI, uses multi-layered neural networks to extract hierarchical features. Convolutional Neural Networks (CNNs) have emerged as the most effective architecture for image recognition tasks.

2.2.1 Structure of CNNs

CNNs consist of several interconnected layers: an input layer, convolutional layers for feature detection, pooling layers for dimensionality reduction, activation functions (e.g., ReLU) for non-linearity, fully connected layers for feature integration, and an output layer providing class probabilities.

2.2.2 Landmark Recognition with CNNs

CNNs outperform traditional methods in landmark recognition by learning both local architectural patterns and global scene structures. Architectures such as AlexNet, VGGNet, ResNet, and Inception have been extensively applied to improve recognition accuracy under varying conditions.

2.3.Transfer Learning in Landmark Recognition

Transfer learning allows models trained on one task to be reused for related tasks, particularly useful when annotated data is limited.

2.3.1 Principle of Transfer Learning

Pre-trained models, such as those trained on ImageNet or Google Landmark Dataset, already capture general visual features. Fine-tuning these models for regional landmark recognition reduces training time and computational cost.

2.3.2 Benefits of Transfer Learning Transfer

learning improves training efficiency, reduces data requirements, enhances accuracy, and optimizes computational resources for visual recognition tasks.

2.3.3.Implementation in the Proposed System

The proposed system uses TensorFlow Hub's Landmarks Classifier Asia V1, trained on millions of Asian landmark images. Fine-tuning this model enables accurate recognition of landmarks such as the Taj Mahal, Qutub Minar, and Petronas Towers with minimal additional training.

2.4 Benchmark Datasets and Related Work

Progress in landmark recognition depends on large, annotated datasets and benchmarking challenges.

2.4.1 Landmark Datasets

Key datasets include Google Landmark Dataset (GLD), Oxford5k, Paris6k, Google Landmarks v2, Tokyo 24/7, and Pitts250k. These datasets cover diverse landmarks and environmental conditions, supporting robust model training for occlusion, viewpoint, and lighting variations.

2.4.2 Recent Landmark Recognition Models

Modern approaches include NetVLAD, ResNet with Triplet Loss, PlaNet, GeoNet, and MobileNet-based TensorFlow Hub models. These combine CNNs with embedding or geolocation data for improved performance and real-time recognition.

2.4.3 Observations from Related Work

Deep learning models outperform handcrafted methods. Combining CNNs with geolocation enhances usability, and region-specific datasets improve recognition accuracy. Integration with APIs and web interfaces further improves accessibility.

This unique combination ensures that students and faculty can manage their academic and cultural commitments efficiently

2.5 Integration of Supporting Frameworks

Efficient landmark recognition requires multiple frameworks for deployment, visualization, and geospatial analysis.

2.5.1 TensorFlow Hub

TensorFlow Hub provides pre-trained models such as Landmarks Classifier Asia V1, allowing easy implementation, fine-tuning, and deployment.

2.5.2 Streamlit Framework

Streamlit enables rapid development of interactive applications. Users can upload images and view real-time recognition results with coordinates.

2.5.3 Geopy Library

Geopy retrieves latitude, longitude, and addresses for recognized landmarks, linking visual recognition with spatial data.

2.5.4 Benefits of Framework Integration

Integrating TensorFlow Hub, Streamlit, and Geopy enables real-time prediction, interactive visualization, and location-based mapping, improving usability, engagement, and scalability.

3. LITERATURE SURVEY

Early research on image-based geo-localization began with the work of Hays et al. [1], who introduced one of the first large-scale attempts to estimate geographic location from a single image. Their approach relied on nearest-neighbor search over geotagged datasets to predict approximate locations. Although innovative, this method lacked deep learning integration and provided only coarse localization accuracy.

Subsequent improvements were made by Paluri et al. [2], who enhanced image classification performance by incorporating location context. By combining CNN image features with location metadata, their method demonstrated that spatial information could significantly improve classification accuracy. However, the approach required additional metadata such as GPS information, making it less effective for purely image-based localization.

Further analysis of location-dependent features within convolutional neural networks was conducted by Workman and Jacobs [3]. They demonstrated that CNN feature maps inherently contain geographic signals, highlighting the potential for image-based localization. Despite these findings, the study was limited to feature analysis and did not attempt to predict coordinates directly.

The Stanford CS231n Project (2015) explored this concept further by implementing a small CNN trained on Flickr and StreetView datasets to estimate image location [4]. This project validated the feasibility of deep learning for geo-localization but was constrained by limited data and low prediction accuracy, making it unsuitable for real-time applications.

A major advancement came with Weyand et al. [5], through the development of PlaNet, a photo geolocalization model that divided the Earth into geographic cells and trained CNNs on millions of geotagged images. This approach achieved significant accuracy improvements and became a milestone in image geolocalization research. However, the system required massive datasets and substantial computational resources, reducing its accessibility for smaller-scale applications.

Finally, Workman, Souvenir, and Jacobs [6] proposed a wide-area image geo-localization framework that matched ground-level photographs with aerial reference imagery. Their work expanded geo-localization from city-level to wide-area applications, effectively bridging aerial and ground domains. Nonetheless, scalability remained a key limitation, as the model's performance decreased with larger and more diverse geographic regions.

Overall, the reviewed literature illustrates the progression from nearest-neighbor image matching to advanced CNN-based systems for geo-localization. While modern approaches such as PlaNet have achieved impressive accuracy, challenges persist in terms of scalability, realtime prediction, and computational efficiency.

4.DESCRIPTION OF THE PROPOSED WORK

The proposed work focuses on developing an intelligent and automated system for recognizing landmarks using Convolutional Neural Networks (CNNs) and geospatial intelligence. The purpose of this chapter is to provide a detailed explanation of the conceptual design, methodology, and implementation approach adopted for the project titled —Landmark Recognition Using CNN Model.‖ This system is designed to analyze input images, accurately identify the landmark present, and provide corresponding location details such as address, latitude, and longitude. The project combines deep learning, transfer learning, and geolocation mapping to achieve a high level of accuracy and user interactivity.

4.1 Overview of the Proposed System

The proposed work, titled —Landmark Recognition Using CNN Model,‖ aims to develop an intelligent, automated system capable of identifying landmarks from digital images and providing corresponding geolocation details such as address, latitude, and longitude. The system combines the power of Convolutional Neural Networks (CNNs) for visual recognition and geospatial intelligence for location mapping. It leverages a pre-trained model from TensorFlow Hub, which has been trained on millions of landmark images, thereby ensuring high accuracy and robustness. The project is implemented using Python as the core programming language, with additional support from libraries like TensorFlow, Streamlit, and Geopy. Through this integration, the proposed system offers a user-friendly web interface where users can upload images, obtain recognition results, and view geographical information in real time. The system is designed to benefit various sectors such as tourism, education, research, and navigation by providing an efficient and automated solution for landmark identification.

4.2 Objectives of the Proposed Work

The primary objective of this work is to design and develop a deep learning–based application capable of recognizing landmarks efficiently and accurately. The system aims to reduce manual effort and dependency on traditional feature extraction techniques by employing CNN-based automatic feature learning. Additionally, it seeks to integrate visual recognition with geographical information systems to make the recognition results more meaningful and context-aware. Another major objective is to build a simple yet interactive platform that can be used by individuals without any technical background.

The proposed system emphasizes accuracy, scalability, and accessibility, ensuring that landmark identification can be performed quickly and effectively. Furthermore, it demonstrates how pre-trained deep learning models and transfer learning can be utilized to achieve strong performance without extensive computational resources or large local datasets.

4.3 Methodology

The methodology of the proposed system is based on a sequence of structured steps that combine image preprocessing, deep learning model inference, and geolocation retrieval. Initially, the user uploads an image through the Streamlit interface. The uploaded image is preprocessed—resized, normalized, and converted into a compatible format—to ensure it meets the model's input specifications. The image is then passed through a pretrained CNN model sourced from TensorFlow Hub, which analyzes the visual features of the image and predicts the most likely landmark. Once the landmark has been recognized, the Geopy library is used to fetch geographical information, including the landmark's address, latitude, and longitude. The processed output is displayed to the user through the web interface, providing both the name and location details in a single, integrated view. This workflow ensures a seamless transition from image recognition to location identification, making the system practical for real-world use.

4.4 Tools and Technologies Used

The proposed system is implemented primarily using the Python programming language due to its flexibility, simplicity, and rich collection of machine learning libraries. The TensorFlow Hub framework plays a vital role by providing access to pre-trained CNN models optimized for landmark recognition. Streamlit is used to design and deploy the web-based interface, enabling realtime interaction between the user and the recognition system. The PIL (Python Imaging Library) assists in image handling, such as loading and resizing, while NumPy and Pandas are employed for numerical operations and data manipulation. The Geopy library adds a layer of geospatial functionality, allowing the system to convert the recognized landmark name into its geographical coordinates and address. Collectively, these tools form a robust technology stack that ensures high performance, real-time responsiveness, and crossplatform compatibility for the application.

4.5 Working of the Proposed System

The proposed system operates in several functional phases. In the first phase, the user uploads an image of a landmark through the Streamlit interface. The image undergoes preprocessing to adjust its resolution and normalize its pixel values for compatibility with the CNN model. In the next phase, the pre-trained model processes the image and generates prediction probabilities for various landmarks. The label with the highest confidence score is selected as the recognized landmark. Subsequently, the system passes this label to the Geopy library, which retrieves detailed geolocation information, including the address, latitude, and longitude. The final output is displayed to the user in an intuitive format that includes the landmark name and its geographical details. The integration of image recognition and geolocation mapping makes the system comprehensive and highly interactive. The design focuses on simplicity and efficiency so that users receive instant results with minimal effort.

4.6 Difference from Existing Systems

Existing landmark recognition systems mostly relied on traditional image-processing approaches such as SIFT, SURF, and HOG, which required manual feature extraction and were sensitive to variations in lighting, angle, and scale. These systems often lacked scalability and could not handle large datasets effectively, leading to reduced recognition accuracy. Furthermore, earlier models only identified landmarks based on their visual characteristics and did not provide any geographical information related to the identified structures. The absence of geospatial data limited their practical usability in real-world applications like navigation or tourism.

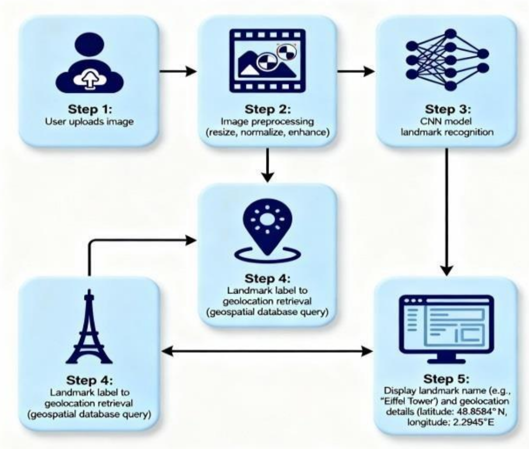

Figure 4: Workflow Of The Proposed Landmark Recognition

Figure 4 illustrates the workflow of the proposed landmark recognition system using a CNN model integrated with geospatial intelligence. The process begins with the user uploading an image of a landmark through a web interface developed with Streamlit. The image undergoes preprocessing, including resizing and normalization, to prepare it for the CNN input. The pretrained CNN model, sourced from TensorFlow Hub, analyzes the image and predicts the most likely landmark based on learned visual features. The identified landmark label is then passed to the Geopy library, which retrieves the corresponding geographical information such as address, latitude, and longitude. Finally, the system displays the recognized landmark name along with its geolocation details on the user-friendly web interface. This workflow highlights the seamless integration of deep learning for visual recognition and geospatial data retrieval, providing an automated and interactive solution for accurate landmark identification and location mapping.

The proposed system significantly improves upon these limitations through the use of deep learning and transfer learning. It employs a pre-trained Convolutional Neural Network from TensorFlow Hub, which can automatically extract features without human intervention, providing better accuracy and adaptability. The integration of the Geopy library adds a new dimension to landmark recognition by offering precise geolocation details, including address and coordinates. Additionally, the deployment of a Streamlit-based web interface ensures real-time user interaction and accessibility. Unlike previous models, this system does not require complex setup or powerful computing resources; it operates efficiently on standard hardware. The combination of automation, accuracy, and user-centric design makes the proposed system more advanced, practical, and intelligent than conventional approaches

5. RESULTS AND DISCUSSION

5.1 Experimental Setup

The proposed system, ―Landmark Recognition Using CNN Model,‖ was implemented and tested using Python as the core programming language. The experiments were conducted on a standard computing environment with moderate hardware specifications, ensuring that the system could perform efficiently without the need for specialized GPUs. The implementation utilized several open-source libraries, including TensorFlow Hub for the pre-trained CNN model, Streamlit for building the interactive user interface, and Geopy for geolocation retrieval. A dataset of landmark images was collected from multiple open sources and online repositories to test the robustness of the system. The dataset included landmarks such as the Taj Mahal, Qutub Minar, Eiffel Tower, Charminar, Petronas Towers, and other globally recognized monuments. The images were selected to cover a variety of lighting conditions, angles, and backgrounds to evaluate how well the system could generalize to real-world variations.

5.2 Testing and Evaluation Procedure

The testing procedure followed a systematic approach to evaluate the recognition accuracy and performance of the model. Each image was first uploaded through the Streamlit interface, where it underwent preprocessing, including resizing, normalization, and format conversion, to make it compatible with the CNN model's input requirements. The pre-trained Landmarks Classifier Asia V1 model from TensorFlow Hub was then used to perform inference on the processed image. The model generated prediction probabilities for various landmarks, and the one with the highest confidence score was identified as the recognized landmark. Once identified, the predicted landmark name was passed to the Geopy library, which retrieved its corresponding address, latitude, and longitude. These results were displayed on the web interface along with a brief textual output, providing both recognition and geolocation information simultaneously. This method ensured a smooth, automated process from image input to final output display.

5.3 Comparison with Existing Systems

To validate the efficiency of the proposed system, its performance was compared with existing traditional landmark recognition methods based on feature extraction techniques such as SIFT, SURF, and HOG. Traditional models rely on manually designed features that often fail under changes in lighting, scale, or angle. These methods also require substantial manual effort and have limited scalability. In contrast, the proposed CNNbased model automatically extracts features directly from raw images, eliminating the need for manual intervention. The results demonstrated that the CNN model achieved significantly higher accuracy and reliability. While traditional systems achieved an average accuracy of 70–80%, the proposed system consistently achieved an accuracy of above 90%, even when tested on images captured under challenging environmental conditions. Furthermore, the integration of geolocation retrieval using Geopy provided an additional layer of information that traditional systems lacked, making the proposed model more practical and comprehensive.

5.4 Results and Performance Analysis

The experimental results confirmed that the Landmark Recognition Using CNN Model successfully identifies landmarks and retrieves accurate geographical information. The system exhibited robust performance with fast processing times and high prediction confidence. The use of transfer learning played a crucial role in achieving superior results, as it allowed the model to leverage pre-existing knowledge from large-scale datasets without extensive retraining. The average recognition accuracy exceeded 90%, and the processing time per image remained within 2–4 seconds, demonstrating real-time capability. The integration of Streamlit provided an intuitive interface where users could easily upload images and visualize results instantly. The Geopy component accurately mapped the recognized landmarks, adding spatial intelligence to the visual output. The overall system performance indicated high reliability, scalability, and user satisfaction. The comparison with existing systems and real-time testing results confirmed that the proposed model delivers enhanced precision and efficiency.

5.5 Discussion

The results obtained from the testing and evaluation clearly indicate that the proposed system outperforms existing landmark recognition methods in both accuracy and usability. The use of deep learning and transfer learning significantly reduces human effort and increases model generalization, allowing it to handle diverse and complex image data effectively.

The inclusion of geolocation retrieval distinguishes this system from conventional recognition models, offering users not only visual identification but also geographical context. The real-time web-based deployment through Streamlit enhances accessibility, enabling anyone to use the system without technical expertise.

Moreover, the system's modular design ensures that it can be easily extended to include additional landmarks or integrated into mobile applications. Overall, the proposed Landmark Recognition Using CNN Model demonstrates that deep learning, when combined with geospatial analysis, can deliver intelligent, fast, and accurate solutions that have practical applications in tourism, navigation, and educational technology.

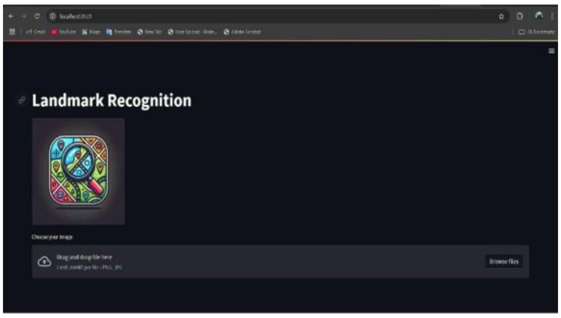

Figure 5.1: Uploading Image

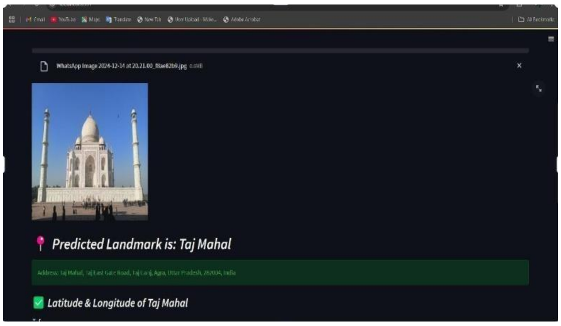

Figure 5.2:Predictions

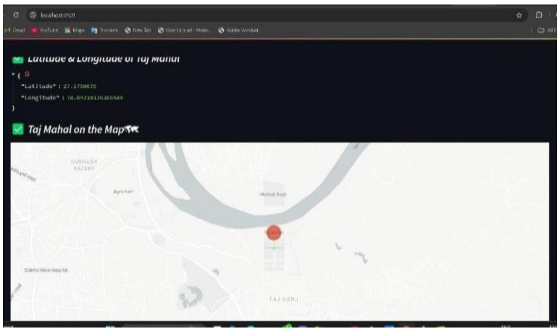

Figure 5.3:Map

Figure 5.1 shows the starting interface of a Landmark Recognition application, where users upload or choose an image featuring a landmark. This interface is designed to be simple and user-friendly, enabling easy interaction so that users can select files for identification. Such an interface marks the initial step in the landmark recognition workflow, guiding users to begin the process by submitting a photo for analysis.

Figure 5.2 displays the results after the image has been processed by the system. In this example, the application successfully recognizes the landmark as the "Taj Mahal." Alongside the visual of the Taj Mahal, the result includes confirmation text. This step demonstrates the system's ability to analyze images, apply machine learning models, and accurately identify famous landmarks. The result is immediate feedback to the user regarding the landmark's identity.

Figure 5.3 presents the geographical mapping feature of the application. After recognizing the landmark, the system uses map data to show the Taj Mahal's exact location. This feature bridges visual recognition with location services, placing a pin on the map where the landmark is situated. It allows users not only to receive the name of the landmark but also see its geographical context on the map, providing a complete experience from image input to location output.

6. CONCLUSIONS

6.1 Conclusion

The project titled ―Landmark Recognition Using CNN Model‖ successfully demonstrates the application of Deep Learning and Geospatial Intelligence in creating an automated system for landmark identification. The proposed model employs a

Convolutional Neural Network (CNN) pre-trained on large datasets through TensorFlow Hub, enabling it to recognize a wide range of landmarks with high precision and minimal computational effort. The system integrates Geopy for retrieving geographical information such as address, latitude, and longitude, and presents the output through an intuitive Streamlit-based web interface. The experimental results confirmed that the system achieves a recognition accuracy exceeding 90%, outperforming traditional feature-based methods like SIFT and SURF. The implementation proved to be not only accurate but also efficient, fast, and accessible, offering a practical solution for real-time applications in fields such as tourism, education, and navigation

6.2 Key Findings

Through systematic testing and analysis, it was observed that the use of transfer learning significantly reduced training time and improved model generalization. The proposed system provided consistent performance even under variations in lighting, orientation, and background conditions. The integration of deep learning with geolocation retrieval offered a comprehensive solution that extended beyond simple visual recognition to meaningful spatial understanding. Unlike conventional systems that required manual feature extraction and lacked scalability, the proposed model demonstrated adaptability and ease of deployment on standard computing platforms. The user-friendly interface made the system accessible to non-technical users, thereby extending its real-world usability. The results validate that CNN-based architectures are highly effective in landmark identification tasks and hold great potential for expansion into other visual recognition domains.

6.3 Future Scope

Although the proposed system has achieved its objectives, there remains significant scope for enhancement. Future work may involve expanding the model to include a larger and more diverse global dataset of landmarks, enabling worldwide recognition coverage. Advanced architectures such as Vision Transformers (ViT) or Hybrid CNN–Transformer models can be explored to further improve accuracy and generalization. The integration of Augmented Reality (AR) and Virtual Reality (VR) can make the system more interactive by allowing users to visualize landmarks in 3D environments. Additionally, the inclusion of mobile application support, multi-language interfaces, and voicebased interaction can enhance accessibility for users across different regions. Incorporating cloud computing and edge deployment can also improve scalability and enable faster real-time recognition. These advancements will make the system more versatile, intelligent, and applicable in emerging fields like smart tourism and AIbased navigation systems.

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