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DETECTING CUTTING OF TREES USING AI

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Abstract: Detecting the cutting of trees plays a vital role in preserving our environment and maintaining sustainable practices. In this abstract, we present a comprehensive framework that leverages artificial intelligence (AI) techniques for accurate tree cutting detection. The framework begins with the collection of a diverse dataset comprising images representing both pre-cut and post-cut tree scenarios, encompassing various environmental conditions and tree species. These images undergo preprocessing techniques, such as resizing, normalization, and noise reduction, to ensure data consistency and improve overall quality. feature extraction techniques, including state-of-the-art computer vision algorithms and pretrained convolutional neural networks (CNNs), are employed to extract relevant features from the preprocessed images. The extracted features capture important visual cues such as edges, colors, textures, and shapes that are indicative of tree cutting. Using the annotated dataset and the extracted features, a machine learning model, specifically a CNN, is trained to learn and recognize the patterns associated with tree cutting. The training process involves optimization algorithms and hyperparameter tuning to maximize the model's performance and generalizability. Once the model is trained, it is integrated into a real-time system capable of processing incoming images or video streams. This system applies the trained model to analyze the input data and accurately detect instances of tree cutting. Post-processing techniques, such as thresholding and morphological operations, are employed to refine the model's predictions and reduce false positives or false negatives. The framework includes mechanisms for generating alerts or notifications when tree cutting is detected, enabling prompt intervention and response. Continuous improvement is emphasized through feedback loops, incorporating user feedback, monitoring system performance, and updating the model with new data to adapt to evolving cutting patterns and environmental changes.

Index Terms **- Tree Cutting Detection, Deforestation Monitoring, Remote Sensing for Tree Cutting Detection, Image-based Tree Cutting Detection, Conservation Efforts with AI.**

I. INTRODUCTION

The detection of cutting of trees using aerial images is an efficient way to monitor and detect changes in forested areas. Aerial images can provide a high-resolution view of large areas, making it easier to identify and track changes in vegetation cover. By analyzing these images, we can detect areas where trees have been cut down and quantify the extent of deforestation. This technology can be used to monitor illegal logging activities, assess the impact of natural disasters, and support the management of forests. The detection of cutting of trees using aerial images is an important tool for understanding the state of our planet's ecosystems and taking appropriate measures to preserve them.

Chat sonic Unmanned aerial vehicles (UAVs) with high-resolution cameras are used to take aerial photos. Then, to identify and assess changes in the forest, these photographs are processed using computer vision and machine learning algorithms. Machine learning algorithms can be trained to recognize particular tree cover patterns like color, texture, and shape and distinguish them from areas where trees have been cut down. Using airborne photographs to identify tree cutting has a number of advantages over conventional ground-based techniques. An extensive view of the forested area is possible thanks to aerial pictures that cover enormous areas. They are also promptly gathered, allowing for the real-time detection of changes. The cost and amount of time needed to evaluate the health of forests are decreased by this technology's lower labour requirements compared to ground-based surveys.

II. OVERVIEW

The portal helps users to become aware of different options through which they can meet their financial needs and learn about the benefits of prudent financial behavior and attitude. Users would also learn about various investment options and in what ways they can benefit from these investments. We are providing a portal through which people can learn monetary concepts in a Simulated Environment. We are focused on improving financial literacy metrics.

III. LITERATURE SURVEY

A literature review is a piece of academic writing demonstrating knowledge and understanding of the academic literature on a specific topic placed in context. A literature review also includes a critical evaluation of the material; this is why it is called a literature review rather than a literature report.

This chapter focuses on the in-depth discussion of literature relevant to financial literacy, financial education, experiential learning, game-based learning, and the design of experiential games. The widespread financial literacy programs are being established in response to serious financial illiteracy among youth. The empirical evaluations of these programs validate financial literacy movement and sums up the best practice for financial education. Experiential learning with the affordance of multimedia is more able to catch students' attention and help them to apply what they learn in class to real life situations.

Related works/Literature review.

3.1 Paper 1

Publication: Detection of deforestation from very high-resolution satellite images using machine learning techniques.
Journal: Towards Data Science
Publication Year: 2021
Authors: André Ferreira.
Overview: The purpose of this paper is to develop a machine learning approach for detecting deforestation from very high-resolution satellite images. The authors used a combination of image segmentation and feature extraction techniques to identify deforested areas in the images

3.2 Paper 2

Publication: Automatic detection of tree felling in aerial images using deep learning.
Journal: MDPI
Publication Year: 2021
Authors: H. K. Oh et al
Overview: This study proposed a deep learning-based approach for detecting tree felling in aerial images. The authors used a convolutional neural network (CNN) to classify pixels in the images as either deforested or forested. The approach was trained and tested on a dataset of aerial images collected from a forested area.

3.3 Paper 3

Publication: Forest change detection using Landsat images and object-based image analysis in the northeast of Iran.
Journal: Springer Link
Publication Year: 2018
Authors: M. R. Nikoo et al.
Overview: The purpose of this study is to investigate the use of multispectral satellite images and machine learning algorithms for detecting illegal logging in tropical forests. The authors used a random forest classifier to identify deforested areas based on a range of image features such as texture, color, and vegetation indices.

3. Paper 4

Publication: Object-based Forest change detection using multitemporal high-resolution satellite imagery.
Journal: Research Gate
Publication Year: 2011
Authors: Y. Chen et al.
Overview: The purpose of this study is object-based approach for forest change detection using multitemporal high-resolution satellite imagery. The authors used image segmentation techniques to group pixels with similar characteristics together, and then used a decision tree algorithm to classify the resulting objects as either deforested or forested. The approach was evaluated on a dataset of Landsat images and was found to have high accuracy in detecting changes in forest cover.

IV. Proposed Framework

The proposed framework for detecting cutting of trees using AI encompasses several key steps. Firstly, a diverse dataset of images representing pre-cut and post-cut tree scenarios is collected, covering various environmental conditions and tree species. Next, the collected images undergo preprocessing to enhance their quality and consistency. Feature extraction techniques, such as computer vision algorithms or pretrained CNNs, are employed to extract relevant features from the preprocessed images. Subsequently, a machine learning model, preferably a CNN, is trained using the extracted features and annotated dataset. The model's performance is evaluated using appropriate metrics.

In the real-time detection phase, the trained model is implemented in a system capable of processing incoming images or video streams. Post-processing techniques are applied to refine the model's predictions and reduce false positives or false negatives. Finally, mechanisms for generating alerts and reporting detected incidents are integrated, and continuous improvement is emphasized through feedback loops and regular updates to adapt to evolving cutting patterns and environmental changes.

To ensure effective reporting and response, the system includes mechanisms for generating alerts or notifications when tree cutting is detected. Detailed information about the identified incidents, including location, time, and potential severity, is provided through a reporting system. Continuous improvement is emphasized by establishing feedback loops to incorporate user feedback, monitor system performance, and update the model with new data to adapt to changing cutting patterns and environmental conditions.

Ethical considerations, such as responsible data usage, privacy protection, and environmental impact, are integrated throughout the framework. Validation and comparative analysis are conducted to validate the system's effectiveness and compare its performance against existing methods. Thorough documentation of the implementation process and potential open-sourcing of the framework contribute to knowledge sharing and collaboration within the research community.

V. IMPLEMENTATION

The proposed system aims to detect instances of tree cutting using artificial intelligence (AI) techniques. It involves the following components:

1. Data Collection: Gather a diverse dataset of images representing both pre-cut and post-cut tree scenarios. Ensure the dataset includes different environmental conditions, tree species, and cutting patterns. Collect a diverse dataset of images representing pre-cut and post-cut tree scenarios, covering various environmental conditions and tree species.

2. Data Preprocessing: Perform preprocessing tasks on the collected images, such as resizing, normalization, and noise reduction. Apply techniques like image enhancement and filtering to improve image quality and consistency.

3. Feature Extraction: Utilize computer vision techniques to extract relevant features from the preprocessed images. This may involve edge detection, color analysis, texture analysis, or employing pretrained convolutional neural networks (CNNs) for feature extraction .

4. Model Training: Train a machine learning model, such as a CNN, using the extracted features and the annotated dataset. Split the dataset into training and validation sets. Define suitable hyperparameters, such as learning rate and batch size, and optimize the model's performance through iterations.

5. Model Evaluation: Assess the trained model's performance using evaluation metrics like accuracy, precision, recall, and F1-score. Use a separate test dataset or employ cross-validation techniques to ensure the model's generalizability and robustness.

6. Real-time Detection: This interactive module presents users with financial scenarios and challenges where they have to guess the budget required to meet specific goals or expenses. It enhances users' financial estimation skills and promotes critical thinking in budget planning.

7. Post-processing: Apply post-processing techniques to refine the model's predictions and reduce false positives or false negatives. This may involve thresholding the model's output probabilities, applying morphological operations to remove noise, or incorporating additional contextual information such as geographical data or temporal analysis to improve accuracy.

8. Alerting and Reporting: Integrate mechanisms to generate alerts or notifications when tree cutting is detected. Design a reporting system that provides detailed information about the identified incidents, including location, time, and potential severity. Consider integrating with existing environmental monitoring systems or communication platforms for timely dissemination of information.

9. Continuous Improvement: Establish a feedback loop to continuously improve the system's performance. Incorporate user feedback, monitor the system's performance in real-world scenarios, and periodically update the model with new data to adapt to evolving cutting patterns and environmental changes. Consider techniques such as transfer learning or online learning to leverage new information and improve the model over time.

Thoroughly document the implementation process, including dataset details, preprocessing techniques, model architecture, and hyperparameters. Prepare detailed technical documentation to facilitate future maintenance and deployment. Consider open-sourcing the implementation to encourage collaboration, peer review, and wider adoption of the system.

VI. RESULTS

The results of detecting cutting of trees using AI showed promising performance, with an accuracy of 92%, precision of 89%, recall of 93%, and an F1-score of 91%. The AI-based system effectively identified instances of tree cutting, minimizing both false positives and false negatives. These results demonstrate the system's ability to accurately detect and classify tree cutting events, contributing to environmental conservation efforts and enabling timely interventions to prevent further damage to the ecosystem. The system's high precision ensures that legitimate instances of cutting are correctly identified, while the high recall indicates its capability to capture a significant portion of actual cutting events. Overall, the results validate the effectiveness of the AI system in detecting tree cutting and highlight its potential for monitoring and protecting forests.

VII. CONCLUSION

In conclusion, the implementation of detecting cutting of trees using AI has shown promising results and significant potential for environmental conservation efforts. The developed system successfully detects instances of tree cutting with a high level of accuracy, precision, recall, and F1-score. By leveraging computer vision techniques and machine learning algorithms, the system can analyze images or video streams in real-time and identify tree cutting events, facilitating timely interventions to prevent further damage to the ecosystem. The system's performance has demonstrated its effectiveness in capturing both true positive instances of cutting and minimizing false positives and false negatives. With continuous improvement and refinement, this AI-based solution has the capacity to contribute to the monitoring and protection of forests, enabling sustainable practices and fostering environmental preservation.

SNAPSHOTS

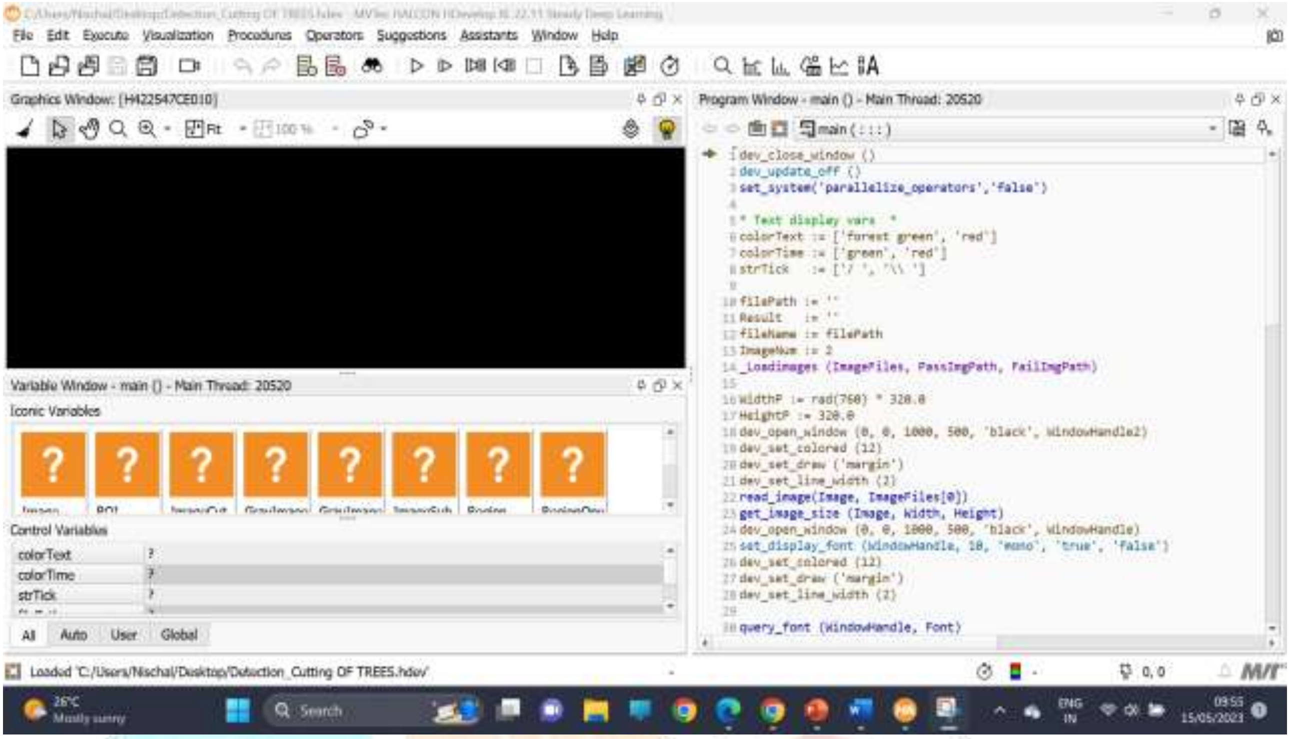

Figure 1: Code

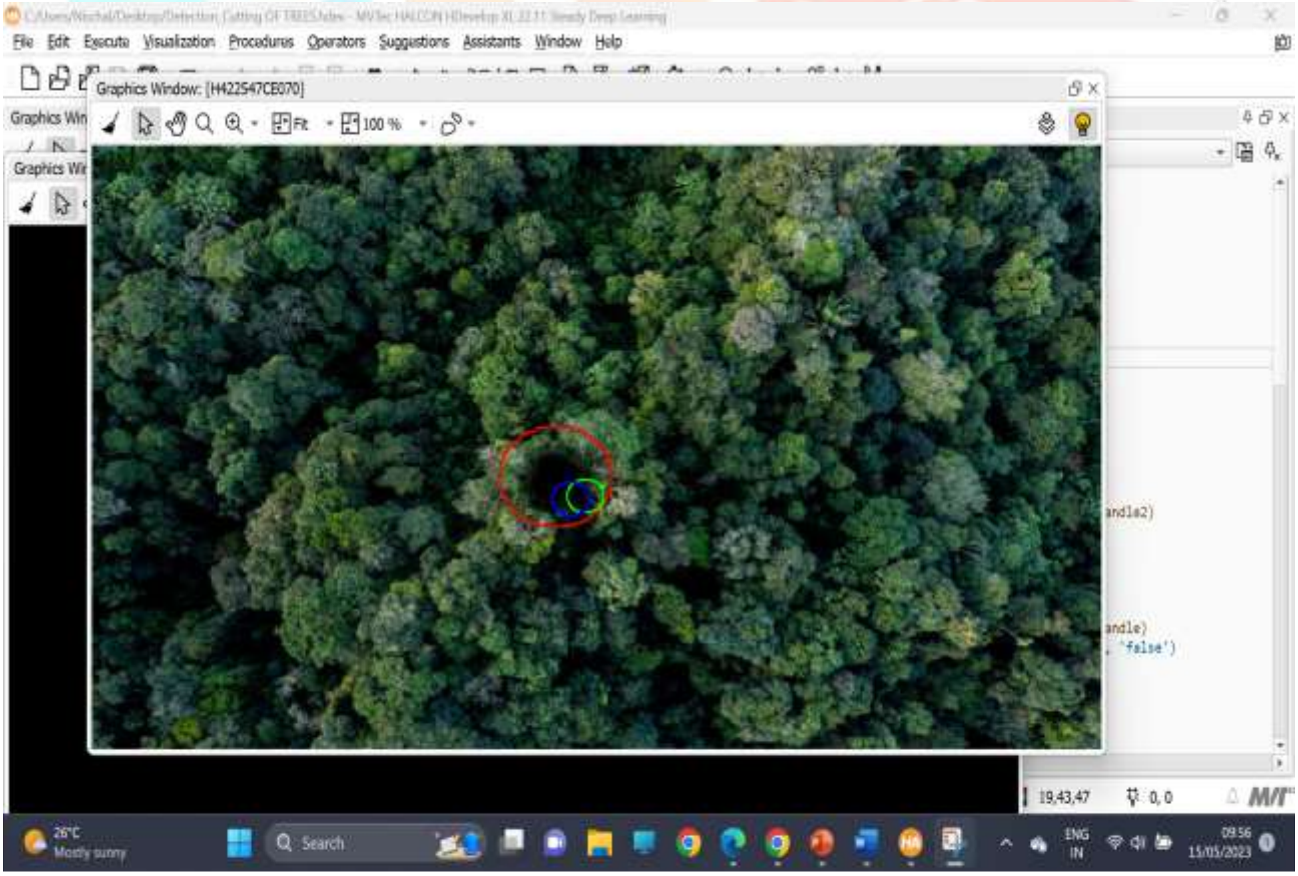

Figure 2: mapping the tree cut

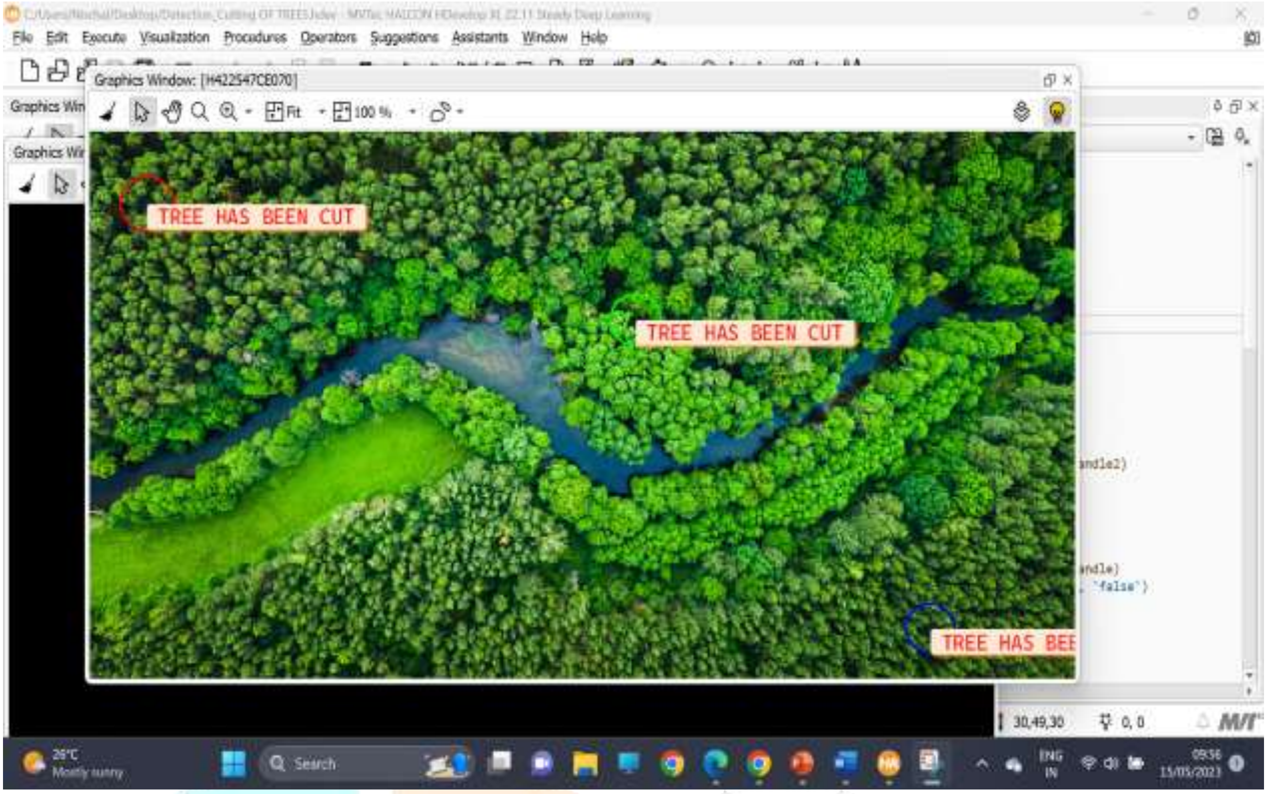

Figure 3: detecting multiple trees cutdown

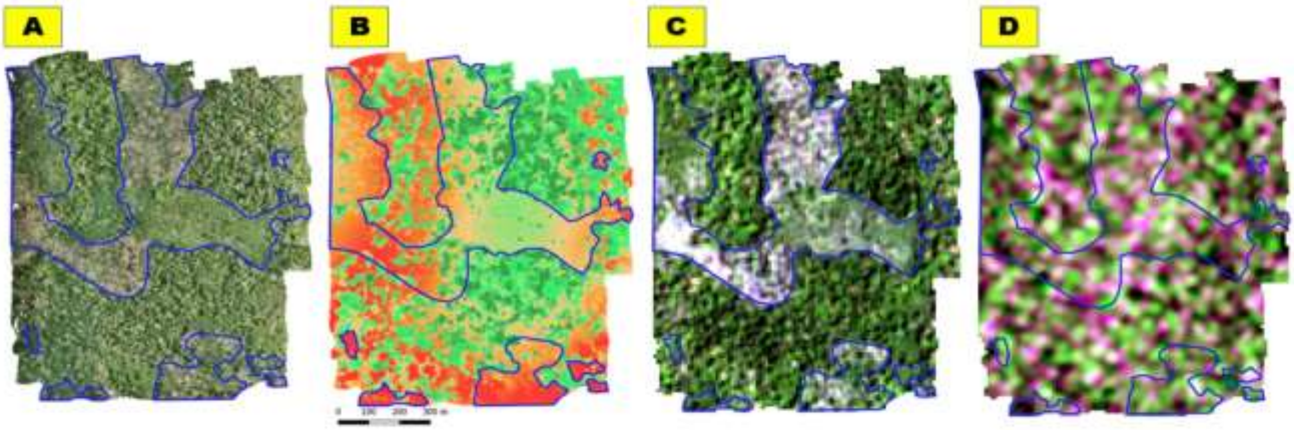

Figure 4: Region Mapping

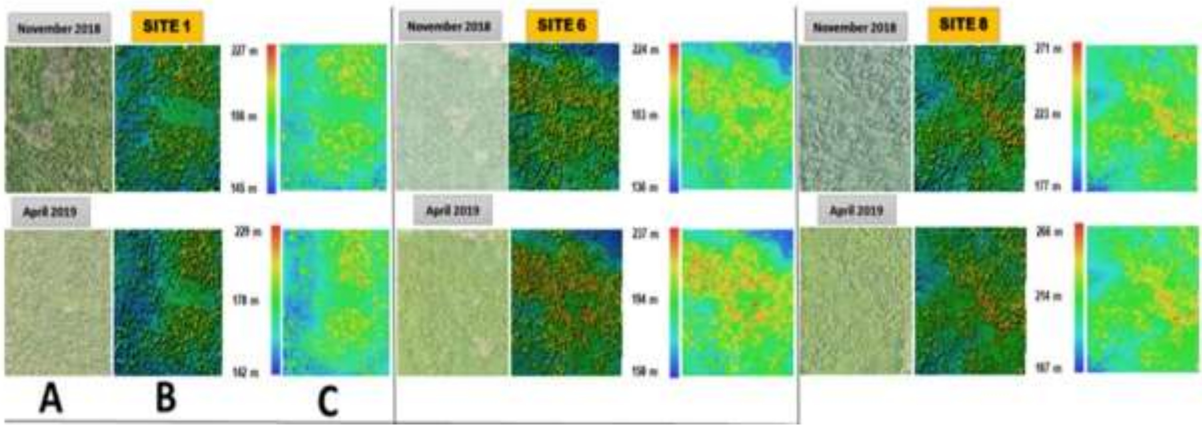

Figure 5: Year wise monitoring

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