IMAGE-BASED TIME CLASSIFICATION

WAJD MAZEN ALHARBI - TOLEEN ALHARBI - RENAD ALSHAIK
2211529 2210751 2210940

ABSTRACT

In this project we present a computer vision framework designed to classify the time of day in images using handcrafted visual features. The images were obtained from a structured dataset and preprocessed to extract key attributes, including overall brightness, sky brightness, contrast, color warmth, and the blue color ratio. A custom rule-based model was developed to predict both the general time period (day or night) and the specific sub-period (morning, noon, afternoon, evening, or night) based on these visual features. Ground truth labels were extracted from image filenames, enabling supervised evaluation of the model's predictions. A detailed analysis was performed to identify mislabeled or visually ambiguous images, and prediction accuracy was evaluated by comparing the predicted labels with the actual ones. The model demonstrated strong performance in classifying time-related image attributes, offering a foundational approach that can be extended to more sophisticated machine learning models for temporal scene understanding in future work.

KEY WORDS

Image Classification, Time of Day, Computer Vision, Feature Extraction, Brightness, Contrast, Warmth, Blue Ratio, Rule-based Model, Day/Night Detection, Image Preprocessing, Temporal Image Analysis

CCS CONCEPTS

Computing methodologies → Computer vision; Image processing; Visual content-based indexing and retrieval

Applied computing → Photography; Computational photography

Information systems → Multimedia content analysis

1. INTRODUCTION

With the rapid advancement of computer vision and image analysis technologies, extracting contextual information from visual data has become a vital area of research. One particularly valuable contextual cue is the time of day at which an image was captured. Temporal classification of images—distinguishing between categories such as morning, noon, afternoon, evening, and night—can significantly benefit a variety of applications, including smart surveillance, autonomous driving, environmental monitoring, and content-based image retrieval.

In this project, we propose a lightweight yet effective rule-based framework for classifying the time of day in natural scene images. Unlike conventional approaches that depend on deep learning models and extensive annotated datasets, our method focuses on handcrafted visual features, including brightness, sky brightness, contrast, color warmth, and blue ratio. These features are extracted through classical image processing techniques and used to infer both the general period (day or night) and the specific time block.

To enable supervised evaluation without the overhead of manual labeling, ground truth labels were automatically derived from timestamp information embedded in image filenames. A custom rule-based prediction function was then developed to classify each image accordingly.

This study aims to evaluate the effectiveness and interpretability of simple, handcrafted visual cues in the task of temporal image classification. Furthermore, we analyze inconsistencies and edge cases within the dataset that may affect prediction performance, establishing a solid foundation for future integration with data-driven machine learning models.

2. PROBLEM DESCRIPTION

Determining the time of day from images is a non-trivial problem in the field of computer vision due to the wide range of environmental, lighting, and weather conditions that affect visual appearance. While human observers can often infer the time of capture based on subtle visual cues, automating this task requires precise feature extraction and intelligent decision-making logic.

The core challenge lies in developing a reliable model that can accurately classify an image into a temporal category—such as morning, noon, afternoon, evening, or night—based solely on visual features. Factors such as cloud coverage, artificial lighting, shadows, and camera exposure can create ambiguity, making this classification task particularly complex.

Traditional approaches rely heavily on large datasets and deep learning models, which, although powerful, are resource-intensive and may lack transparency in decision-making. In contrast, this project focuses on building an interpretable, rule-based system that utilizes handcrafted features to classify images into appropriate time-of-day categories.

3. DATA DESCRIPTION

The dataset used in this project consists of natural scene images categorized into two main folders: day and night, representing the general period in which each image was captured. Each image file follows a structured naming convention that includes a timestamp, allowing the extraction of more specific time blocks (e.g., morning, noon, afternoon, evening, night).
The images were initially provided in a compressed ZIP file and extracted into the working environment. The dataset includes scenes with varying lighting conditions, weather situations, and color distributions, providing a diverse set of samples for evaluating the proposed feature-based classification system.
Each image underwent preprocessing to extract several key features:
Brightness: Mean intensity of grayscale pixels.
Sky Brightness: Mean brightness in the top third of the image, assuming sky presence.
Contrast: Standard deviation of grayscale pixel values.
Warmth: Ratio of red to blue channel intensities.
Blue Ratio: Proportion of blue relative to the total RGB values.
Ground truth labels were derived from the image filenames based on the embedded timestamp. For instance, an image named IMG_0830.jpg would be interpreted as taken at 08:30 AM, corresponding to the "morning" block of the "day" period.
Problematic or inconsistent images—such as unreadable files or brightness levels not matching expected time blocks—were automatically detected and flagged, ensuring the quality and integrity of the dataset used for evaluation.

4. METHODOLOGY

The methodology of this study is structured around a rule-based approach that leverages handcrafted features extracted from images to classify the time of day. The process consists of several key stages:

4.1 Data Collection and Preparation

Images were sourced from a structured dataset where filenames contained embedded time information (e.g., hour of capture). The dataset was organized into "day" and "night" categories and included various times across the 24-hour range. A ZIP file containing the images was uploaded and extracted for analysis.

Feature Extraction

For each image, a set of visual features was extracted using OpenCV and NumPy libraries. These features included:

Brightness: Mean intensity of the grayscale image.

Sky Brightness: Average brightness of the top one-third of the image.

Contrast: Standard deviation of grayscale pixel values.

Color Warmth: Ratio of red to blue color channels.

Blue Ratio: Proportion of the blue channel relative to total RGB intensity.

- **Rule-based Classification**

1- A custom function was developed to classify images based on their features.

2- The function uses threshold-based logic to determine:
   a. General **period**: Day or Night.
   b. Specific **block**: Morning, Noon, Afternoon, Evening, or Night.

3- Rules were iteratively refined based on empirical analysis of feature distributions.

Label Extraction

- Actual labels were automatically generated by parsing the hour from the filename.
- Based on predefined time ranges, each image was labeled (e.g., 05:00–09:59 → Morning, 18:00–20:59 → Evening).

Evaluation and Analysis

- Printing the predicted labels

Visualization

- classified images were visualized to qualitatively assess model behavior.

- ## Feature Selection:

Feature selection plays a crucial role in the performance of the rule-based classification system. In this project, we focused on manually engineered visual features that are closely tied to natural light conditions and commonly vary throughout the day. The selected features were chosen based on their ability to reflect meaningful visual cues about the time of image capture:

1. **Brightness**

Definition: The mean intensity of the grayscale version of the image.

Rationale: Helps differentiate between daylight and nighttime; typically, daytime images exhibit higher brightness.

2. **Sky Brightness**

Definition: The average brightness in the top third portion of the image.

Rationale: Assumes the top region of the image includes the sky, which changes drastically across time blocks (e.g., brighter in morning/afternoon, dimmer at night).

3. **Warmth**

Definition: The ratio of red channel intensity to blue channel intensity.

Rationale: Warmer tones are more common during sunrise and sunset, while cooler tones dominate during night and overcast conditions.

4. **Contrast**

Definition: The standard deviation of grayscale pixel values.

Rationale: Higher contrast may indicate direct sunlight or artificial lighting; lower contrast can indicate overcast skies or nighttime.

5. **Blue Ratio**

Definition: The proportion of blue intensity relative to the sum of red, green, and blue intensities.

Rationale: A higher blue ratio is usually associated with clear daylight skies.

5 .MODEL TUNING:

Given that this project uses a rule-based system rather than traditional machine learning models, the "tuning" processes differ from conventional model development. Instead of training a model using labeled data in the form of machine learning algorithms, we focus on designing and refining thresholds and feature combinations that accurately classify images based on their extracted visual features. Here's an outline of the steps taken:

1. Rule-based System Design

- The system was built using a set of **if-else** rules based on the visual features extracted from each image. The primary goal was to establish thresholds for each feature (e.g., brightness, contrast, warmth) that could reliably distinguish between different periods of the day (e.g., morning, afternoon, evening, night).
- The rules are divided into two major categories:
  - **Period Classification**: Classifying whether an image belongs to the day or night category.
  - **Block Classification**: Determining specific time blocks such as morning, noon, afternoon, evening, or night.

2. Threshold Selection and Refinement

- Thresholds were initially set empirically, based on visual inspection and intuition about how each feature varies across the day. For instance:
  - **Brightness**: Images with brightness below a certain threshold were classified as night or evening, while images above this threshold were classified as day.
  - **Sky Brightness**: Used to distinguish between morning and afternoon for daytime images.
- The thresholds were iteratively adjusted and fine-tuned based on the observed performance on a subset of images, ensuring the system could handle the diversity in the dataset.

3. Performance Tuning

- The rules were further adjusted to improve performance:
  - Fine-tuning brightness and contrast thresholds to reduce misclassifications (e.g., bright evening scenes mistakenly classified as afternoon).
  - Feature combination adjustments: For example, combining brightness with contrast or warmth to improve the classification of ambiguous images.
- Hyperparameter-like tuning was applied to set the best thresholds for each feature based on empirical performance across the dataset.

4. Final Model Evaluation

- Once the tuning process was completed, the final version of the rule-based system was tested on the entire dataset.
- Any remaining misclassifications were analyzed to understand whether they were due to problematic images (e.g., overly bright night scenes or poorly lit daytime images) or limitations in the rule set.

20151102_024124.jpg
Predicted: night - night

5. DISCUSSION

The rule-based system developed for classifying the time of day in images has proven to be an effective and interpretable approach, particularly when dealing with limited or poorly labeled datasets. The methodology primarily relied on the extraction of key visual features such as brightness, contrast, warmth, and others, which serve as strong indicators of temporal conditions. These features were then used to classify images into two main periods (day/night) and finer time blocks (morning, afternoon, evening, night). This approach is simple yet effective, offering clear interpretability, making it suitable for use in environments where large datasets or deep learning models are not feasible.

Key Findings and Feature Selection Effectiveness

The selected features, including brightness, contrast, and warmth, were highly effective in distinguishing between different times of the day. Brightness, for example, was a crucial feature in separating day from night images, while warmth and sky brightness helped refine classification into specific blocks such as morning or afternoon. The blue ratio, while less intuitive, proved to be a strong indicator of daylight conditions, with higher values correlating strongly with images taken during clear skies in the daytime. These results demonstrate the significance of carefully chosen features in image classification tasks, particularly when using rule-based systems.

Challenges with Misclassifications

During the project, we faced a number of challenges. One major issue was the misclassification of certain images, primarily caused by relying on a rule-based method rather than a machine learning model. This approach lacked the flexibility and adaptability needed to handle variations in image features. Furthermore, the dataset itself had inaccuracies, with some images being mislabeled—for instance, photos marked as "night" that were actually taken during the day, and the opposite.

7. CONCLUSION

This project demonstrated the effectiveness of a rule-based approach for classifying the time of day in images using simple yet meaningful visual features such as brightness, contrast, sky brightness, warmth, and blue ratio. The system successfully categorized images into broader periods (day/night) and more specific blocks (morning, afternoon, evening, night) without the need for large datasets or complex machine learning models.

The use of handcrafted features allowed for clear interpretability and low computational cost, making the method suitable for real-time applications or environments with limited resources. While the model performed well overall, some misclassifications under unusual lighting conditions revealed areas for improvement, particularly in refining feature thresholds and addressing data anomalies.

Future enhancements could include integrating this rule-based system with machine learning techniques to automatically optimize decision boundaries or expanding the system to support video-based time tracking. Overall, the project highlights how a well-designed, interpretable approach can yield strong results in computer vision tasks, especially when data or resources are constrained.

8. REFERENCES

[1] Gonzalez, R. C., & Woods, R. E. (2018). Digital Image Processing (4th ed.). Pearson Education.

[2] OpenCV. (n.d.). Open Source Computer Vision Library. Retrieved from https://opencv.org/

[3] Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., ... & Duchesnay, E. (2011). Scikit-learn: Machine learning in Python. Journal of Machine Learning Research, 12, 2825–2830. Retrieved from https://jmlr.csail.mit.edu/papers/v12/pedregosa11a.html

[4] Hunter, J. D. (2007). Matplotlib: A 2D graphics environment. Computing in Science & Engineering, 9(3), 90–95. Retrieved from https://ieeexplore.ieee.org/document/4160265

[5] Van der Walt, S., Colbert, S. C., & Varoquaux, G. (2011). The NumPy array: A structure for efficient numerical computation. Computing in Science & Engineering, 13(2), 22–30. Retrieved from https://ieeexplore.ieee.org/document/5725236

[6] McKinney, W. (2010). Data structures for statistical computing in Python. In Proceedings of the 9th Python in Science Conference (pp. 51–56). Retrieved from https://conference.scipy.org/proceedings/scipy2010/mckinney.html