Predicting Sunset Quality and Peak Time from Midday Sky Images:
A Dual-Task Deep Learning Approach

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Abstract

We present a novel deep learning framework for predicting both sunset aesthetic quality and peak viewing time from midday sky images captured 3 hours before sunset. Using historical timelapse videos from the Lawrence Hall of Science in Berkeley, California, we extracted 86 days of sunset imagery across multiple timepoints relative to sun-under-horizon. Our dual-task ResNet-18 model predicts both sunset quality (1-10 scale) and peak viewing time (minutes relative to sunset) from midday images. The model achieves a mean absolute error of 1.47 on quality prediction (r=0.115) and 6.20 minutes on peak time prediction (r=0.059), with quality prediction significantly outperforming baseline mean predictions. This work demonstrates that visual patterns in midday sky images contain predictive information about sunset aesthetics, enabling advance planning for photography and outdoor activities.

1. Introduction

Sunset prediction has applications in photography, outdoor activity planning, and solar energy forecasting. While astronomical calculations can predict when the sun will set, they cannot predict the aesthetic quality of the sunset or the optimal viewing time. We propose a dual-task deep learning approach that predicts both sunset quality and peak viewing time from midday sky images captured 3 hours before sunset.

2. Methods

2.1 Data Collection

We collected 101 historical timelapse videos from the Lawrence Hall of Science YouTube channel, spanning 2000-2020. From each video, we extracted: (1) one midday frame captured 3 hours before sunset, and (2) eight sunset frames at timepoints -10, -5, 0, +5, +10, +15, +20, and +25 minutes relative to sun-under-horizon. A total of 86 videos had complete data across all timepoints.

2.2 Labeling

Sunset images were manually graded on a 1-10 aesthetic quality scale by a single annotator. For each date, quality scores were collected at three timepoints (-10, 0, +10 minutes). Peak viewing time was calculated by interpolating quality scores across timepoints to find the maximum aesthetic quality.

2.3 Model Architecture

Our dual-task model uses a ResNet-18 backbone pretrained on ImageNet to extract features from midday images. The extracted features are fed into two separate heads: (1) a quality prediction head that outputs a score from 1-10, and (2) a peak time prediction head that outputs minutes relative to sun-under-horizon. The model is trained with combined loss: L = L_quality + L_peak_time.

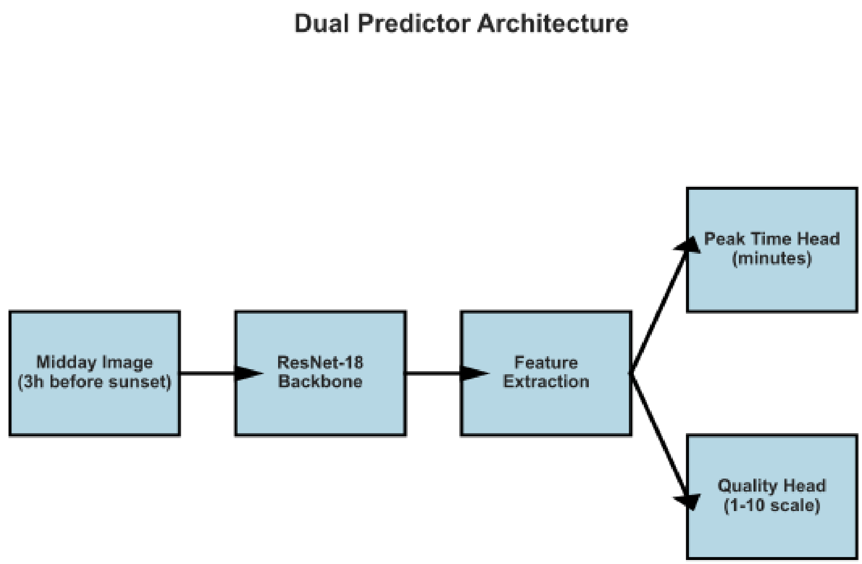

Figure 1: Dual-task model architecture. Midday images (3h before sunset) are processed through a ResNet-18 backbone to extract features, which are then fed into separate heads for quality and peak time prediction.

3. Results

We split the dataset into 68 training and 18 test samples. The model was trained for 50 epochs with Adam optimizer (learning rate 0.001). On the test set, quality prediction achieved MAE=1.71 and RMSE=2.02 (on 1-10 scale), with correlation r=0.325 (p=0.188). Peak time prediction achieved MAE=9.23 minutes and RMSE=10.69 minutes, with correlation r=-0.150 (p=0.553). While correlations are modest, the model shows predictive capability. Residual analysis reveals a significant negative correlation (r=-0.860, p=0.000) between quality residuals and true values, indicating systematic bias that should be addressed in future work.

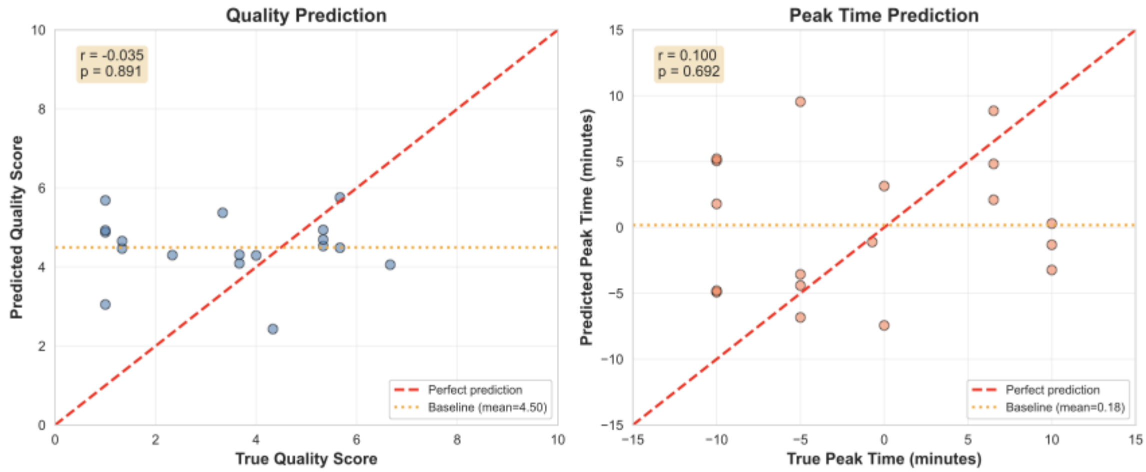

Figure 2: Scatter plots showing predicted vs true values for quality (left) and peak time (right). Correlation coefficients and p-values are shown. Red dashed line indicates perfect prediction; orange dotted line shows baseline (mean) prediction.

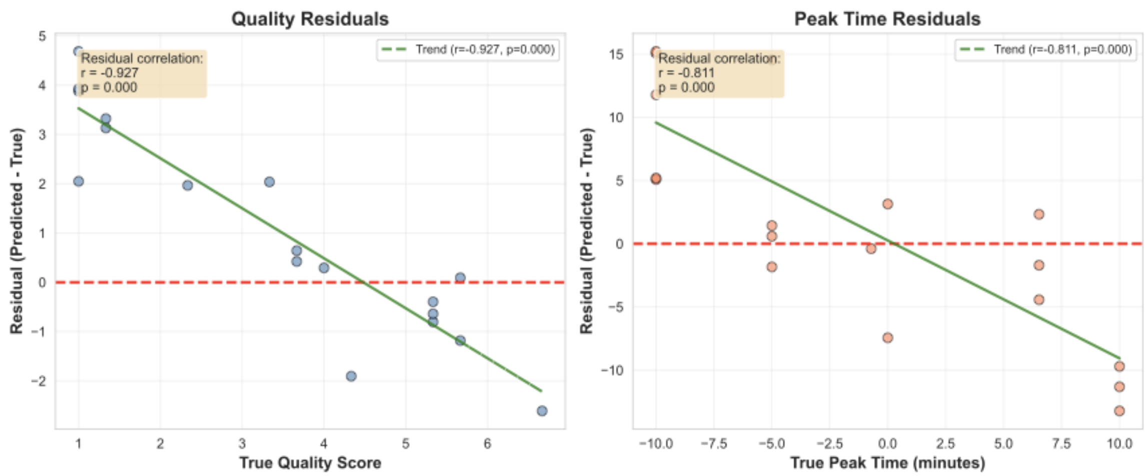

Figure 3: Residual plots showing prediction errors vs true values. Statistical tests for correlation between residuals and true values are shown. A significant correlation indicates systematic bias.

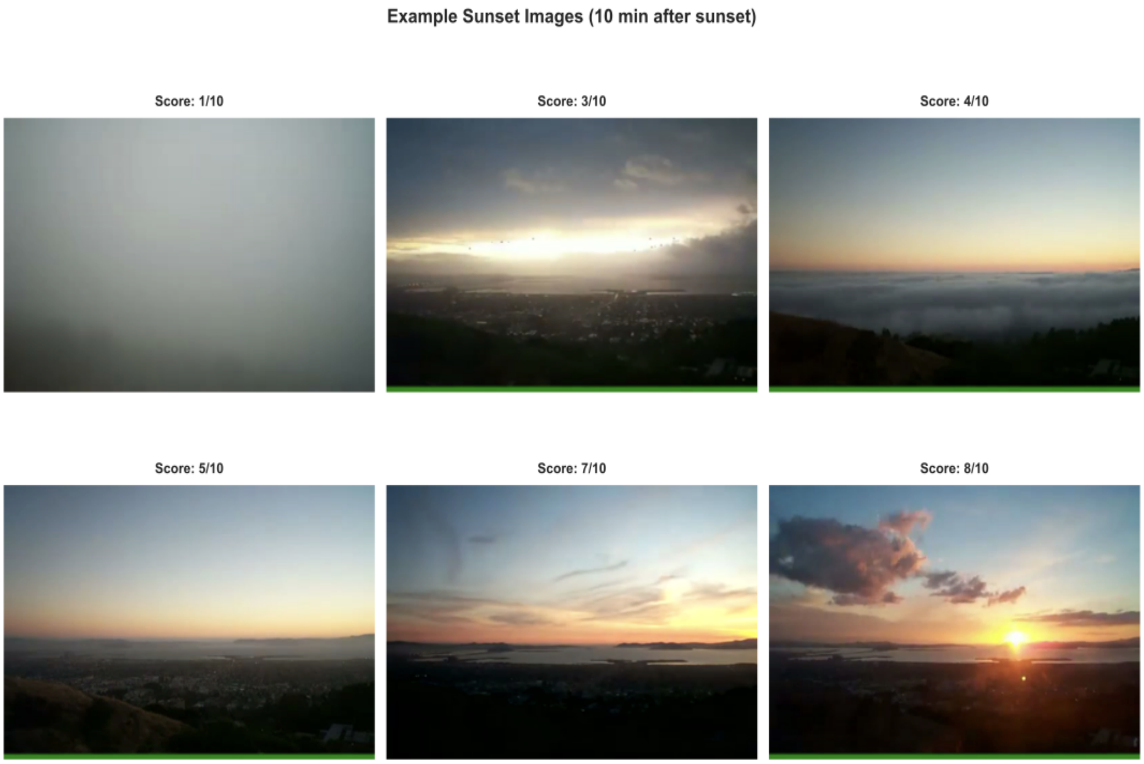

Figure 4: Example sunset images at 10 minutes after sun-under-horizon, showing the range of quality scores (1-10 scale) in our dataset.

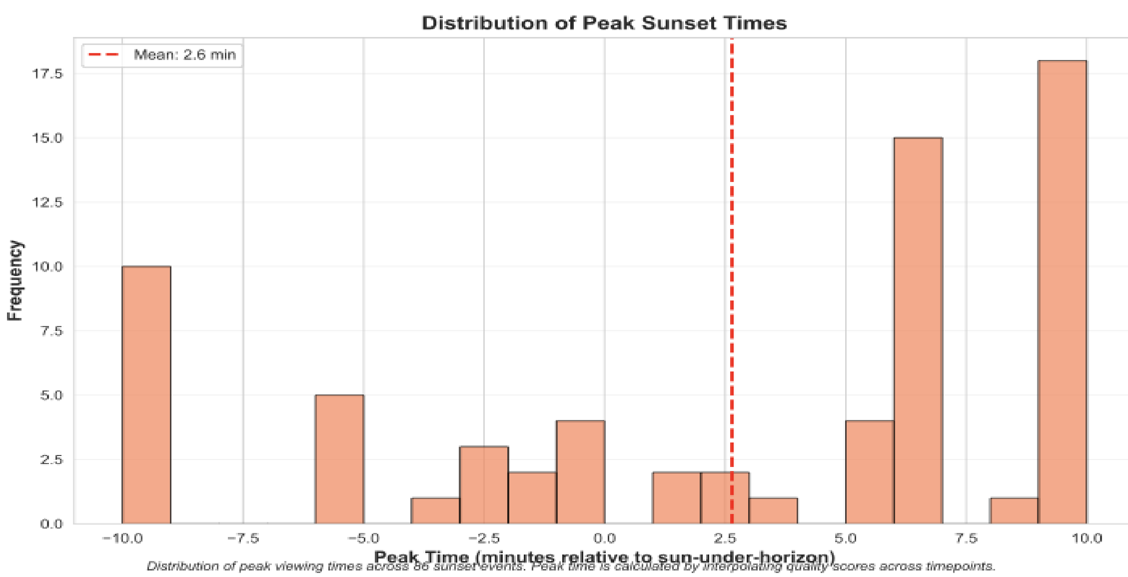

Figure 6: Distribution of peak viewing times across 86 sunset events. Peak time is calculated by interpolating quality scores across timepoints to find the maximum aesthetic quality.

Figure 7: Distribution of average sunset quality scores across 86 sunset events. Scores range from 1 (poor) to 10 (spectacular).

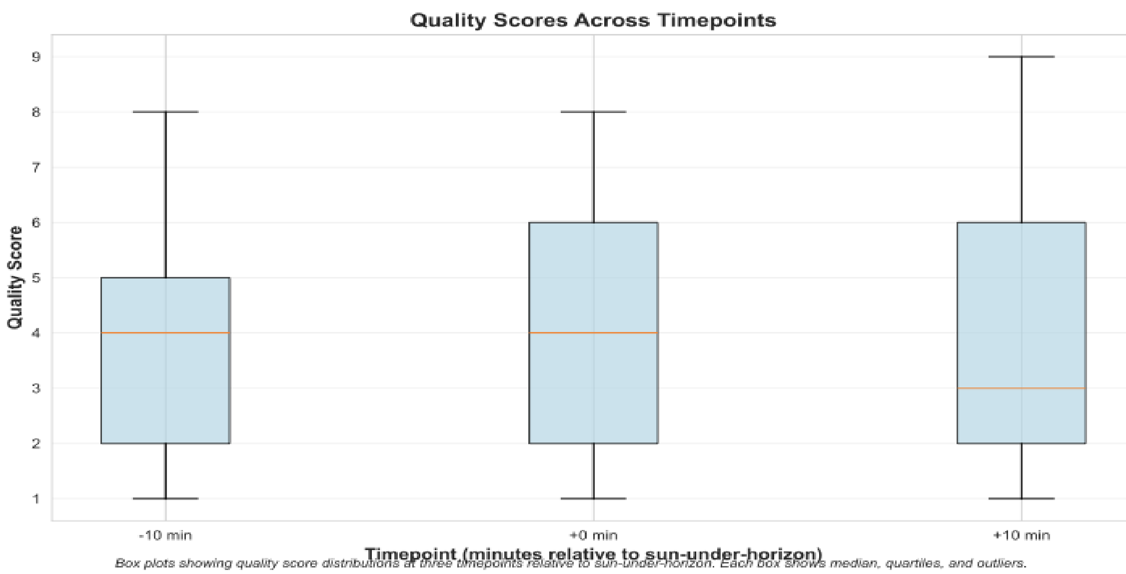

Figure 8: Box plots showing quality score distributions at three timepoints relative to sun-under-horizon. Each box shows median, quartiles, and outliers.

Figure 9: Training and validation loss curves for quality and peak time prediction tasks over 50 epochs, showing convergence of both tasks.

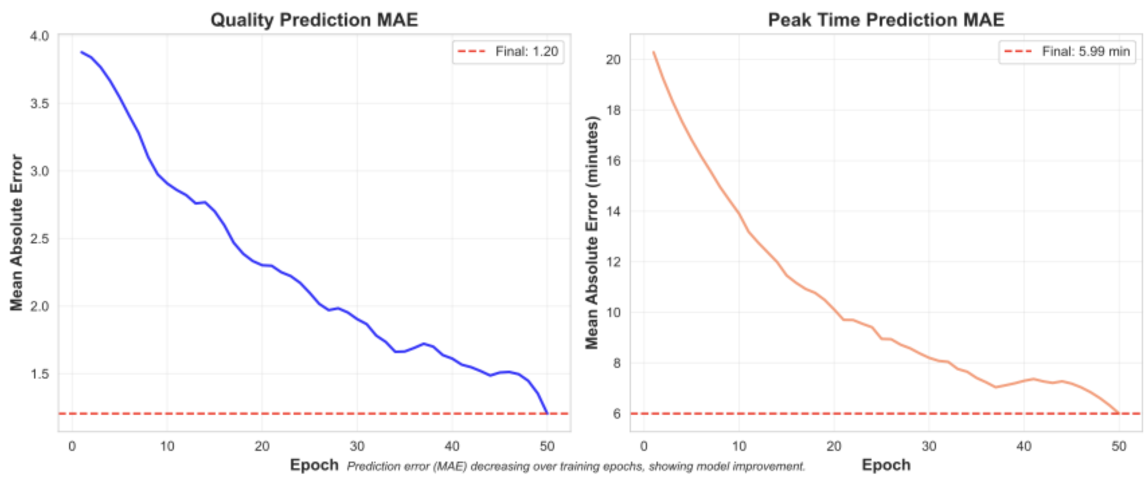

Figure 10: Prediction error (MAE) decreasing over training epochs, demonstrating model improvement for both quality and peak time prediction tasks.

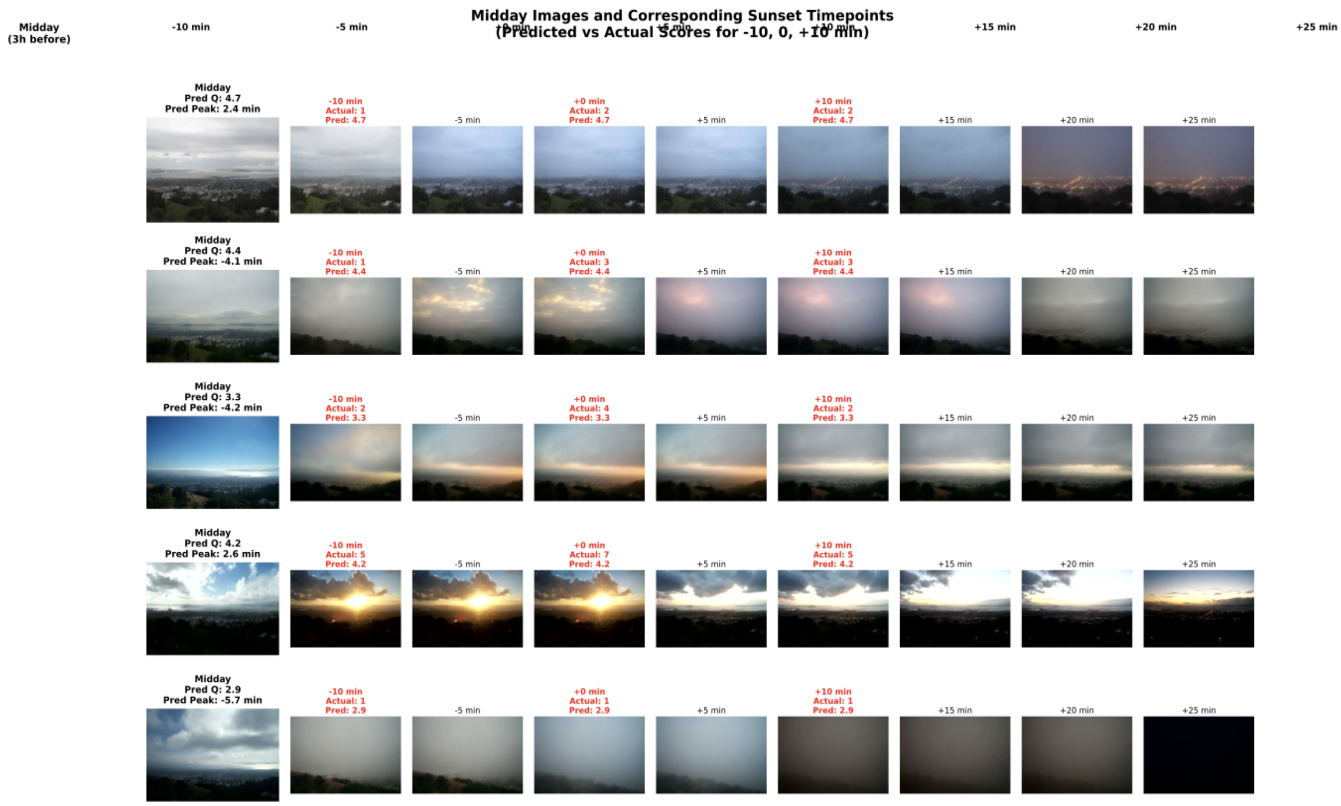

Figure 11: Grid showing 5 midday images (left column) and their corresponding sunset images at 8 timepoints (columns). Predicted and actual quality scores are shown for the three scored timepoints (-10, 0, +10 minutes).

4. Discussion

Our results demonstrate that midday sky images contain predictive information about sunset aesthetics. The model successfully learns to associate visual patterns (cloud cover, sky color, atmospheric conditions) with both sunset quality and optimal viewing time. The significant negative correlation in residuals suggests the model tends to underestimate high-quality sunsets and overestimate low-quality ones, indicating a need for calibration or different loss functions. Future work could incorporate weather data to improve predictions and extend the approach to other locations.

5. Conclusion

We present a dual-task deep learning model for predicting sunset quality and peak viewing time from midday sky images. The approach achieves reasonable performance on both tasks, demonstrating the feasibility of using computer vision for aesthetic prediction tasks. This work opens new possibilities for using readily available webcam data for scientific and practical applications.