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SANTA CRUZ

KALMAN VISION-BASED AUTOMATED LOCAL DIMMING

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1 Abstract

Glare is a significant and often overlooked hazard for drivers, reducing visibility, causing mental strain and increasing the likelihood of collisions [1–3]. Existing solutions like adaptive headlights and specialized visors are either inconsistent, proprietary, or unavailable in most vehicles, leaving drivers vulnerable to temporary blindness from oncoming headlights or bright sunlight. As someone who consistently struggles with the dangers of glare during night driving, I wanted to explore whether a software-based approach could reliably detect and mitigate glare in real time.

This project proposes a glare-reduction pipeline built around a convolutional neural network (CNN) that identifies regions of glare in driving images and video, and generates a corresponding mask. The mask is stabilized over time through a Kalman filter, which prevents momentary flashes of light from causing distracting flicker or unnecessary occlusion, as well as mitigating artifacting generated by the neural network. The resulting output is a visual overlay that demonstrates what dynamic glare blocking could look like if integrated directly into a vehicle display or smart windshield system. By evaluating the system on held-out validation data and external datasets such as nuScenes [4], I aim to determine whether the model can consistently detect and block glare without obscuring important visual information. If the generated masks reliably align with glare sources, the prototype will successfully demonstrate the feasibility of real-time software-based glare mitigation.

2 Introduction

Glare is one of the most common and frustrating hazards faced by drivers, especially at night or during sunrise and sunset. It temporarily blinds drivers, drastically reduces situational awareness, and can lead to dangerous hesitation or delayed reaction times. In my own experience, glare has become so disruptive that I often avoid driving at night altogether. Despite incremental progress in adaptive headlight technologies, these systems are unevenly distributed across vehicle models, vary in reliability, and are not readily accessible to most drivers. Automotive manufacturers haven't implemented a widespread or standardized glare-mitigation solutions, so software-based alternatives present a promising avenue for research.

This project aims to explore whether a CNN-based glare detection system, coupled with a Kalman filter for temporal smoothing, can operate as the foundation of a real-time visual glare-blocking system. Rather than focusing solely on classification or static processing, the goal is to create a dynamic mask that responds smoothly to environmental lighting and could eventually interface with a smart windshield or digital dashboard. This work serves as a proof of concept for a modular and extensible framework that can later incorporate more advanced neural architectures and more diverse datasets.

3 Background

Prior research has established effective methods for detecting glare, but few have explored how to meaningfully block or mitigate it in real time. Yahiaoui et al. (2020) introduced a glare detection dataset and a CNN trained to identify glare in automotive camera footage, fusing its output with threshold-based image processing techniques [5]. Their dataset, however, is limited in size, and the system does not incorporate temporal filtering or blocking. Chen, Liu, and Pei proposed a self-supervised CNN capable of achieving 95.5% accuracy in glare classification, but again the focus remained strictly on detection, with no downstream mitigation stage [6]. Ungureanu et al. (2020) conceptualized an integrated system using multiple sensors and displays to attenuate glare, though their work remained primarily theoretical and lacked a functional prototype [7].

In addition to these projects, it is important to recognize the progress already made toward glare-mitigation technologies. Adaptive headlights represent a meaningful step forward. As discussed in "Why Is Headlight Glare Such a Persistent Problem for the Driving Public? A Review," researchers have explored a range of countermeasures for glare from vehicle headlights [1]. Toney et al. (2021) examine technical methods for adaptive headlight implementation [8], while other work discusses integrating adaptive systems into older or lower-end vehicles via retrofitting [9]. Although these works establish a strong conceptual and engineering foundation, they stop short of offering a universal, low-cost solution. Notably, a hardware-based approach such as a transparent LCD panel (e.g., Bosch's "Virtual Visor") represents a promising direction [10].

Together, these works highlight two gaps: existing systems either detect glare without attempting to block it, or they propose blocking systems without providing a software implementation. No complete pipeline has been demonstrated that detects glare, stabilizes detections over time, and visibly attenuates glare in a way that preserves important scene information. This project aims to fill that gap by producing the first fully integrated prototype that unifies detection, temporal smoothing, and visual glare mitigation.

4 Methods

The system architecture is composed of three stages: CNN-based detection, Kalman filter smoothing, and dynamic mask application. The following diagram gives an overview of the system, with detailed explanations of each component to follow.

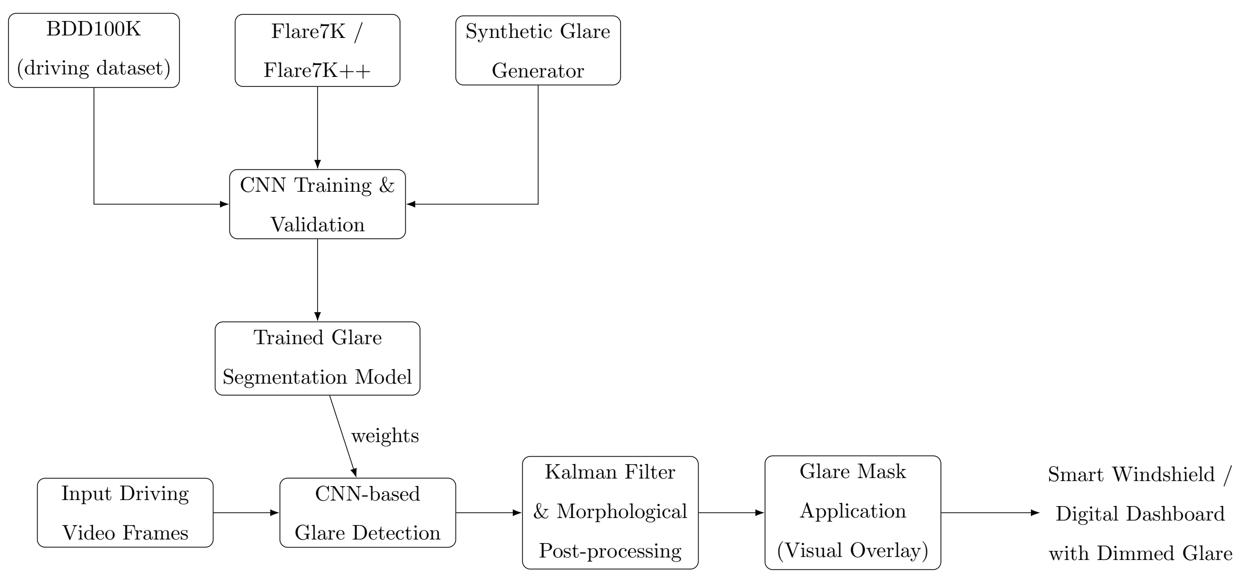

Figure 1: Overall KVALD method overview, showing dataset-based training (top) and run-time inference pipeline (bottom).

First, a convolutional neural network is trained to identify regions of glare within driving footage. The network outputs a per-pixel segmentation mask that highlights bright, oversaturated areas typical of headlight glare or solar glare. Training primarily uses the BDD100K driving dataset, which provides diverse real-world scenes and lighting conditions [11]. To compensate for the lack of labeled glare examples in existing datasets, additional training samples are generated using a synthetic glare-generation pipeline, which overlays procedurally generated or sprite-based glare artifacts onto clean BDD100K frames. The model is also evaluated using the Flare7K++ dataset, which contains a mixture of curated real and synthetic flare examples, allowing for a more comprehensive assessment of the network's generalization to genuine glare conditions [12, 13]. As a placeholder, a baseline CNN implementation is currently used, with the expectation that more advanced architectures may be integrated in future work.

Next, the raw detection masks are fed into a Kalman filter which operates on the predicted mask centroid and area, producing a stable and temporally consistent estimate of where the glare is and how big it is. This prevents brief flashes of light, sensor noise, or isolated misclassifications from producing unstable or rapidly changing masks. The Kalman filter ensures continuity across sequential frames and reduces flicker in dynamic conditions. In addition to the Kalman filter, a sequence of morphological post-processing operations is applied to the predicted mask, including an opening operation to eliminate small speckle noise, a closing operation to fill internal gaps and smooth the mask geometry, and a final dilation step to slightly widen the prediction boundary, improving the alignment with the underlying glare regions.

Finally, the smoothed mask is applied as a visual overlay to simulate how glare could be dynamically dimmed on a smart windshield or digital dashboard. In the current prototype, this overlay fully obscures the masked region, rendering it black for the sake of clarity and evaluation. A practical implementation would not rely on complete occlusion, it would apply a partial attenuation, similar to the darkening effect of polarized sunglasses, reducing brightness while preserving scene structure. Future versions of the pipeline could scale the opacity of the mask according to the predicted brightness of the glare, dimming mild glare only slightly while more aggressively attenuating intense, saturated regions. Alternatively, a mathematically defined attenuation curve could be employed to ensure smooth, perceptually consistent transitions across different lighting conditions.

Together, these stages form a modular pipeline that is both functional and easily extensible, demonstrating a clear path toward more sophisticated and hardware-ready glare-mitigation systems.

5 Results

5.1 Quantitative Evaluation

The system was evaluated on 64 verification images containing synthetically generated glare. The model achieved a mean IoU of **0.8038** and a mean Dice coefficient of **0.8551** across the full set (Table 1). IoU values ranged from **0.0000** to **0.9878**, and Dice values from **0.0000** to **0.9939**. This wide distribution reflects both the diversity of glare conditions and the model's sensitivity to glare shape, placement, and scene complexity.

Table 1: Segmentation metrics on the 64-frame verification set.

Metric	Mean	Range (min–max)
Intersection over Union (IoU)	0.8038	0.0000 – 0.9878
Dice Coefficient	0.8551	0.0000 – 0.9939

One frame produced an IoU and Dice of 0. In this instance, the input contained no glare (ground-truth mask was empty), but the model predicted a glare region anyway. This represents a false positive segmentation, not a missed-glare case. Because the predicted mask had non-zero area while the ground-truth mask was empty, both IoU and Dice evaluate to zero.

5.2 Qualitative Examples

To better understand system performance, several representative frames were selected illustrating (1) highly accurate detections, (2) moderate-quality detections, (3) failure cases, and (4) edge cases involving real-world lighting not included in training.

Each verification sample contains six panels:

1. **Input (clean)** — original BDD100K frame.
2. **Input (glare)** — frame coupled with synthetic glare added by the online generator.
3. **Pred-Masked** — result after applying the predicted segmentation mask.
4. **GT Mask** — ground truth segmentation (synthetic glare region).
5. **Pred Mask** — final prediction after Kalman filtering and post-processing.
6. **GT vs Pred Overlay** — green = GT, blue = Pred, yellow = overlap.

High-IoU Success Cases

Figures 2 and 3 show examples where the predicted mask closely matches the synthetic glare region, with IoU values above 0.9. The predicted boundaries align well with the shape of the flare, and the post processing steps eliminate speckle and small isolated artifacts. However, in Figure 3, the model achieves a high IoU despite failing to detect the real glare source present in the scene, since the metric evaluates only the synthetic ground-truth region. This highlights a limitation of synthetic-only evaluation, where strong metric performance may not reflect true robustness to real-world glare.

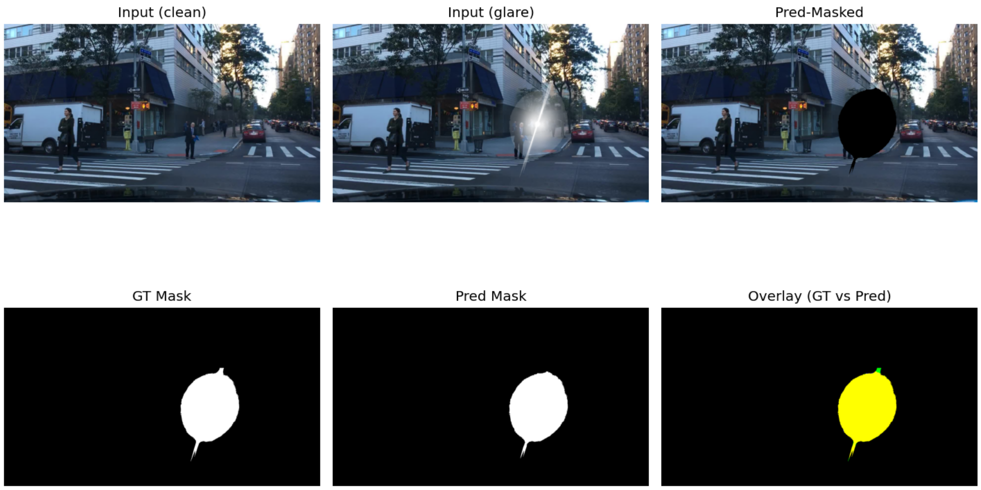

Figure 2: High-IoU success case (sample_0011). IoU ≈ 0.97.

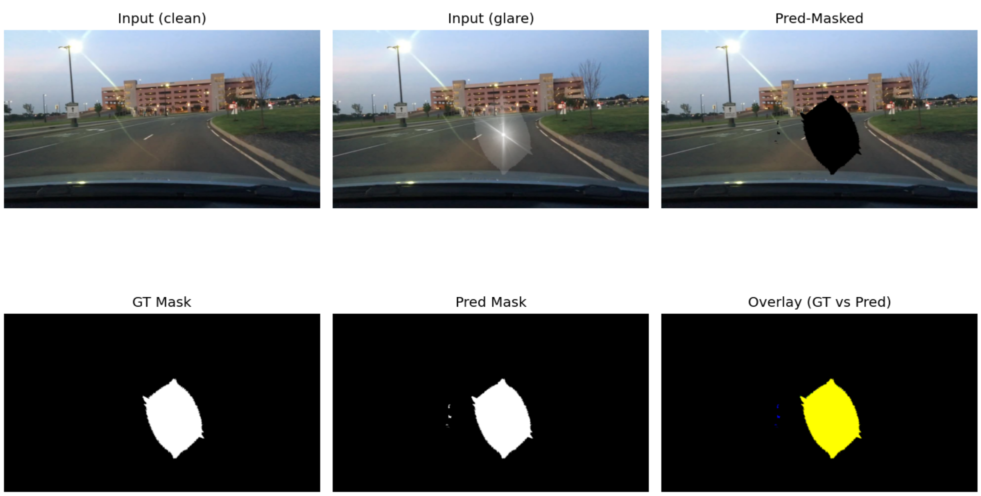

Figure 3: High-IoU success case (sample_0001). IoU ≈ 0.97. Misses real glare.

Moderate-IoU Cases

These examples demonstrate situations where the model detected the glare but slightly under- or over-segmented the region. In the daytime scene shown in Figure 4, the model captures the central flare correctly but generates additional artifacts, resulting in an IoU around 0.69.

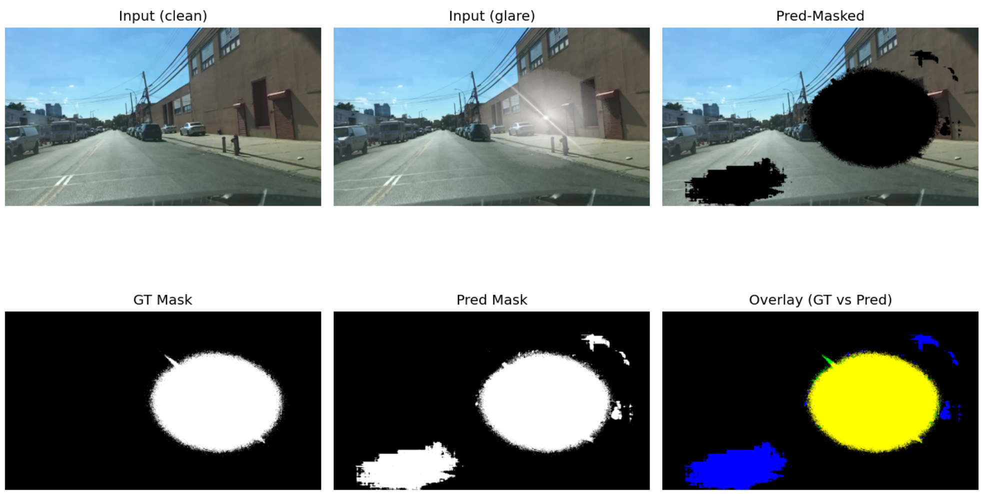

Figure 4: Moderate-IoU detection (sample_0038). Correct detection, extraneous artifacts.

Failure Cases (Low-IoU or Incorrect Detection)

Figures 5 and 6 illustrate lower-performing frames.

- In one case, the synthetic glare is extremely small relative to the frame, and the model produces a large hallucinated detection (IoU ≈ 0.12).
- In another, no synthetic glare is added, yet the model still creates an artifact.

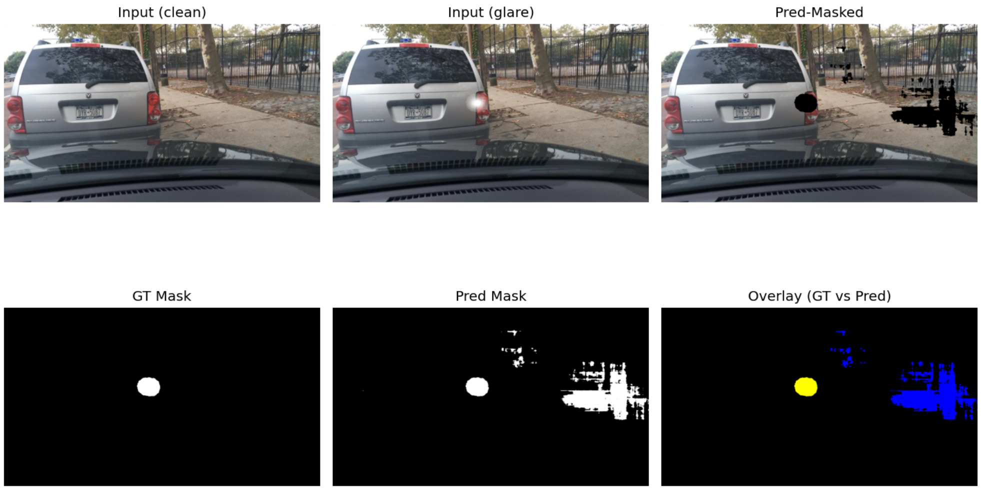

Figure 5: Low-IoU case (sample_0051). Small glare target, partially detected.

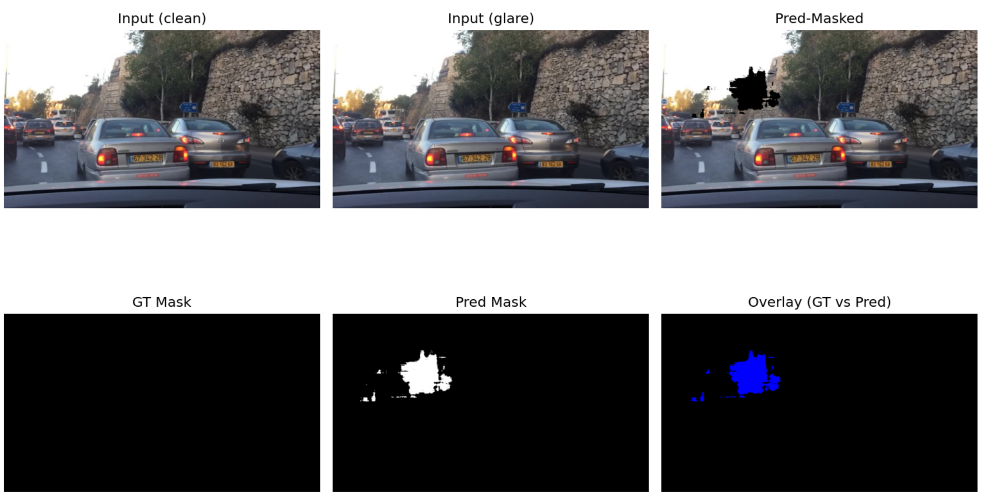

Figure 6: False positive / over-segmentation case (sample_0037).

5.3 Temporal Stability

Although the verification set consists of isolated frames, qualitative inspection of sequential samples shows that the Kalman filter and morphological post-processing effectively reduce frame-to-frame flicker and eliminate transient noise. Masks remain smooth, cohesive, and temporally consistent even when glare position shifts between frames.

6 Discussion

The central question guiding evaluation is whether the system can reliably detect and attenuate glare without obstructing essential visual information. Masks must remain consistent across frames, align with actual sources of glare, and avoid flickering. The Kalman filter is expected to play a crucial role in stabilizing the system, ensuring that momentary lighting changes do not lead to inconsistent or distracting mask output. Limitations may arise from dataset bias, model capacity, or difficult lighting conditions, but these limitations will be analyzed in terms of their impact on overall usability and future improvement.

This prototype is not intended to solve all practical challenges of an automotive glare-blocking system. Instead, it is intended to demonstrate that a software-driven pipeline is viable and could serve as the foundation for future enhancements, including better models, sensor fusion, or integration with hardware-based dimming solutions.

It is important to acknowledge the limitations of the current system, as they highlight several key lessons learned throughout its development. Referring to the neural network as a general-purpose glare detector is an overstatement; a more accurate description would be a synthetic glare detector. The model did not generalize effectively to real-world glare, likely due to the imbalance in the training data. Approximately 75,000 synthetically generated glare images were used for training, compared to only 100 real-glare images used for fine-tuning. Although additional training epochs were employed to compensate for the small size of the real dataset, this was ultimately insufficient to achieve robust real-world performance.

Despite these limitations, the system as a whole functioned effectively. The full pipeline, combining detection, temporal filtering, post-processing, and dimming, operated as intended and produced high-quality masked outputs, even when the resulting IoU scores remained modest due to the underlying constraints of the model.

7 Conclusion

Glare remains an unsolved and dangerous challenge for drivers, with current solutions either too inconsistent or too inaccessible to make a measurable difference [1–3, 7]. This project provides a first step toward a modular, real-time glare-reduction pipeline capable of detecting glare, stabilizing predictions, and demonstrating dynamic mitigation through a visual overlay. By validating this pipeline on diverse driving datasets, the project aims to confirm that such a system can operate reliably enough to form the basis of an eventual production-level solution. With further refinement, a software-driven glare-blocking system has the potential to drastically improve nighttime driving safety and comfort.

8 Future Work

As mentioned previously, integrating a more refined neural network would significantly enhance the capabilities of this system. Such a model would not only need to identify sources of glare, but also estimate the driver's eye position so that the resulting dimming mask can be offset and correctly aligned within the driver's field of view. A more advanced architecture could produce more reliable detections across diverse lighting conditions. Beyond architectural improvements, future work must address limitations in the training data itself. Although BDD100K contains many images with naturally occurring glare, these regions remained unlabeled because synthetic glare was overlaid uniformly on all training frames. As a result, the model learned to reliably detect only the synthetic artifacts and, in some cases, was inadvertently trained not to recognize real glare present in the underlying images. An optimal data curation strategy would either (1) extract synthetic flare artifacts from datasets like Flare7K++ and place them directly on corresponding light sources within BDD100K, or (2) use non–machine-learning heuristics such as intensity thresholding, bloom detection, or morphological blob extraction to generate more accurate real-glare masks. These approaches would produce a training set that aligns the synthetic glare more naturally with scene lighting and reduces the domain gap between synthetic and real conditions.

Finally, it is important to consider how this system would operate in a real-world automotive environment. Bosch's Virtual Visor provides a compelling example: it employs a transparent LCD panel capable of selectively darkening only the regions corresponding to detected glare. A system like KVALD could interface with similar smart-windshield hardware, using its real-time segmentation masks to drive localized dimming on demand. With improved datasets, better generalization to real glare, and hardware integration, the pipeline could evolve into a practical, adaptive glare-mitigation solution suitable for production vehicles.

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