

Real-time Physics-based Removal of Shadows and Shading from Road Surfaces

Bruce A. Maxwell Casey A. Smith Maan Qraitem Ross Messing Spencer Whitt
Nicolas Thien Richard M. Friedhoff
Tandent Computer Vision
bmaxwell1@tandent.com

1. Supplemental Videos

We provide 15 videos demonstrating the performance of our log chromaticity greyscale projection in real-world conditions. These 15 sequences are exemplary selections from the 62 sequences from which the training and testing images were selected and labeled. The 15 videos here are selected to provide a wide variety of road and illumination conditions.

Video01.mp4: Removing shadows cast by other vehicles on the freeway with clear blue skies and dark shadows.

Video02.mp4: A backup camera application removing shadows from the car being driven and other vehicles and buildings on new asphalt.

Video03.mp4: Removing shadows cast by guardrails and signs.

Video04.mp4: The effects of direct glare on the lens : the lens flares present in the original images are also present in Grey Projection.

Video05.mp4: Driving moments before sunset with a strong blue color in the shadows.

Video06.mp4: Concrete road

Video07.mp4: Almost completely overcast with very faint shadows

Video08.mp4: Complex shadows from trees

Video09.mp4: Urban conditions with complex inter-reflection illumination from sunlight reflecting off of building windows. The lens flare remains after processing (as expected) but the shadows are still removed or greatly reduced.

Video10.mp4: Somewhat overcast with complicated tree and power line/pole shadows

Video11.mp4: Tree shadows and some lens glare

Video12.mp4: Complicated tree shadows with imperfect removal: sometimes shadows appear slightly inverted with the shadowed area brighter than the lit. However, such imperfections still allow for the significant gains in white paint recognition rates: images from this sequence and others like it appear in both the train and test sets.

Video13.mp4: Freeway overpass shadow

Video14.mp4: Urban driving with many shadows cast by buildings and parked cars.

Video15.mp4: New dark asphalt

2. ISD Detection

Here, we provide visualizations of the ISD detection process described in the paper. We illustrate the ISD detection on several images to demonstrate how it rejects cars and non-road in the frame.

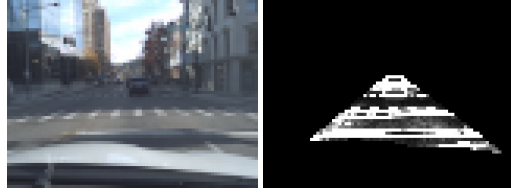
The basic steps for the ISD detection are:

1. Shrink the image
2. Find potential lit and shadowed pixels (restricted to pixels in a trapezoid with low local variance and with some color restrictions – see paper)
3. Dilate the potential lit and shadowed pixels
4. Find potential ISDs based on locations where the dilated potential lit and shadow pixels overlap and where the gradient is large enough and a local maximum.
5. Find the dominant ISD from the list of potential ISDs
6. Calculate a confidence

Figure 1 illustrates the process on an urban road image with building shadows. **Figure 2** illustrates the process on a tree shadow. **Figure 3** illustrates the process on a shadowless image. **Figure 4** illustrates the process on an image with a car dominating the frame. **Figure 5** illustrates the process on an image captured while turning such that most of the frame is off the road.

3. Test Set and Results

We also include the test set images and classification results from the RF classifier in **Figure 6**, **Figure 7**, **Figure 8**, **Figure 9**, **Figure 10**, **Figure 11**, **Figure 12**, **Figure 13**, and **Figure 14**.



(a) Shrunk Image

(b) Local Percent Variance



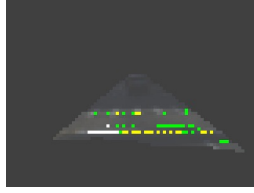
(c) Potential Shadow Pixels

(d) Potential Lit Pixels



(e) Dilated Shadow Pixels

(f) Dilated Lit Pixels



(g) Proposed ISDs

0.671173 0.588012 0.451407	0.660846 0.596897 0.45497
0.686963 0.588159 0.426791	0.661561 0.596242 0.454788
0.682788 0.5898 0.431203	0.652784 0.592306 0.472278
0.675682 0.595049 0.435167	0.654144 0.59399 0.468264
0.684727 0.595766 0.419776	0.652815 0.592854 0.471547
0.672442 0.591488 0.444931	0.652815 0.592854 0.471547
0.672619 0.588947 0.448023	0.654363 0.593331 0.468794
0.638065 0.590976 0.493579	0.658628 0.59479 0.460906
0.659045 0.595384 0.459541	0.659363 0.591457 0.464131
0.664779 0.594631 0.452198	0.659043 0.591609 0.464393
0.66888 0.592389 0.449082	0.657879 0.59262 0.464755
0.66555 0.591235 0.455505	0.656219 0.579649 0.483097
0.664552 0.592639 0.455137	0.656219 0.579649 0.483097
0.66619 0.592982 0.452286	0.656219 0.579649 0.483097
0.660718 0.590789 0.463054	

(h) List of Proposed ISDs

Figure 1. In (a), the image is shrunk to a width of no more than 150 pixels, while computing the local variance shown in (b). Pixels with low variance and suitable colors for lit and shadow pixels are shown in (c) and (d). Those pixels are dilated in (e) and (f). Local gradient maxima with overlapping dilated lit and shadow pixels from (e) and (f) are tested for ISD suitability in (g): White is a big enough gradient but lit-shadowed is too small; light blue is too neutral; dark blue, magenta, and yellow are off the daylight axis; green passes and is a proposed ISD. The list of proposed ISDs is shown in (h). The dominant value is (0.663, 0.591, 0.459). Because all 29 proposed normals agreed, the confidence is 0.9999 (a high number of agreeing detected normals leads to high confidence).



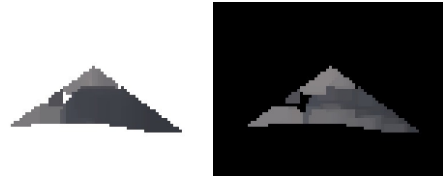
(a) Shrunk Image

(b) Local Percent Variance



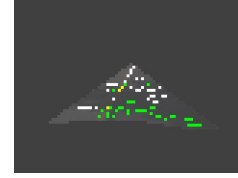
(c) Potential Shadow Pixels

(d) Potential Lit Pixels



(e) Dilated Shadow Pixels

(f) Dilated Lit Pixels



(g) Proposed ISDs

0.621057 0.583013 0.523817	0.634198 0.586644 0.503629
0.617842 0.584795 0.52563	0.635541 0.591161 0.496605
0.63695 0.582305 0.505189	0.665615 0.578006 0.472088
0.654744 0.583009 0.481053	0.633939 0.584311 0.506658
0.654744 0.583009 0.481053	0.653186 0.582416 0.48388
0.645821 0.585807 0.489638	0.639218 0.588656 0.494859
0.630617 0.587215 0.507445	0.627825 0.589354 0.508426
0.638953 0.579857 0.505474	0.629673 0.585577 0.510501
0.633545 0.587868 0.503023	0.622623 0.589788 0.514286
0.639491 0.588861 0.494261	0.628091 0.586962 0.51086
0.644012 0.587076 0.4905	0.611649 0.595934 0.520335
0.660525 0.574931 0.482867	0.619763 0.600194 0.50563
0.631524 0.585242 0.508595	0.619763 0.600194 0.50563
0.634198 0.586644 0.503629	0.631037 0.592738 0.500454
0.63559 0.585381 0.503343	0.631037 0.592738 0.500454
0.638827 0.58459 0.500155	0.631037 0.592738 0.500454
0.633693 0.5853 0.505824	0.631037 0.592738 0.500454
0.632977 0.584917 0.507161	0.631037 0.592738 0.500454
0.633939 0.584311 0.506658	0.631037 0.592738 0.500454

(h) List of Proposed ISDs

Figure 2. In (a), the image is shrunk to a width of no more than 150 pixels, while computing the local variance shown in (b). Pixels with low variance and suitable colors for lit and shadow pixels are shown in (c) and (d). Those pixels are dilated in (e) and (f). Local gradient maxima with overlapping dilated lit and shadow pixels from (e) and (f) are tested for ISD suitability in (g): White is a big enough gradient but lit-shadowed is too small; light blue is too neutral; dark blue, magenta, and yellow are off the daylight axis; green passes and is a proposed ISD. The list of proposed ISDs is shown in (h). The dominant value is (0.635 0.587 0.502). Because all 37 proposed normals agreed, the confidence is 1.0 (a high number of agreeing detected normals leads to high confidence).

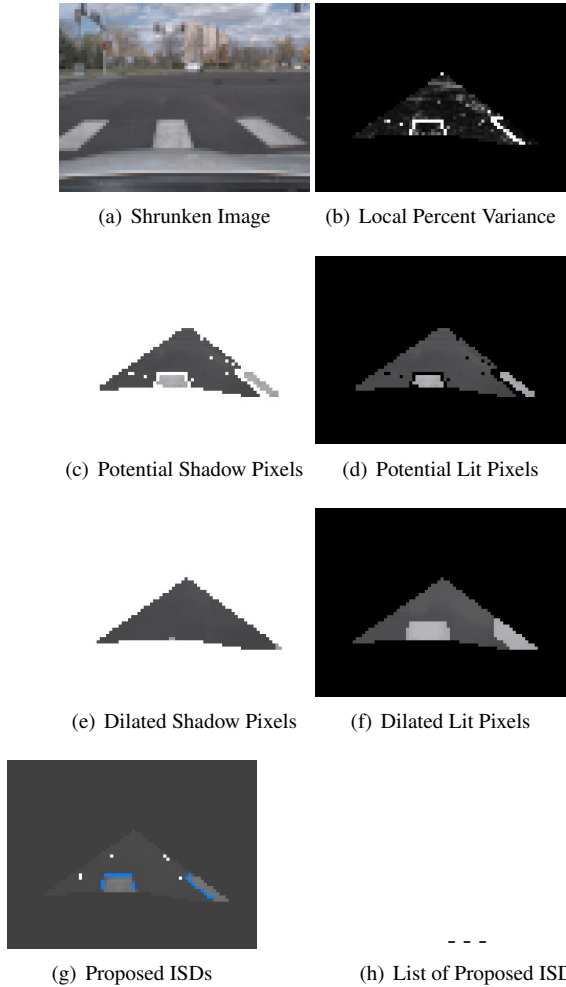


Figure 3. In (a), the image is shrunk to a width of no more than 150 pixels, while computing the local variance shown in (b). Pixels with low variance and suitable colors for lit and shadow pixels are shown in (c) and (d). Those pixels are dilated in (e) and (f). Local gradient maxima with overlapping dilated lit and shadow pixels from (e) and (f) are tested for ISD suitability in (g): White is a big enough gradient but lit-shadowed is too small; light blue is too neutral; dark blue, magenta, and yellow are off the daylight axis; green passes and is a proposed ISD. There are no proposed ISDs because all the edges around the paint are neutral. The list of proposed ISDs is shown in (h). Since there are no proposed ISDs, the confidence is 0, and the Kalman filter is not updated.

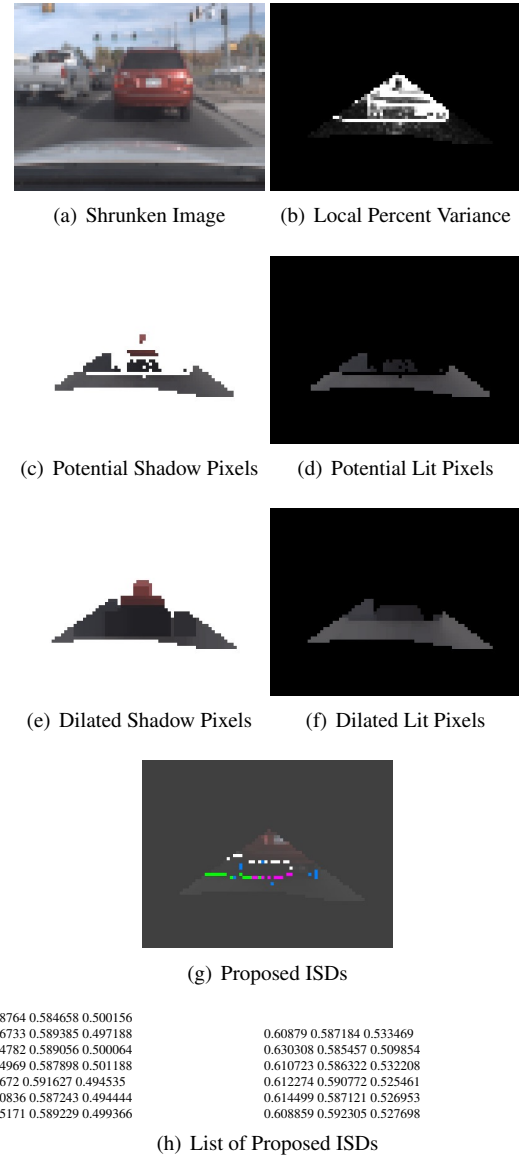
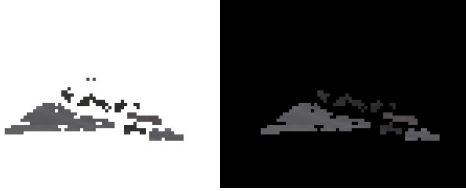


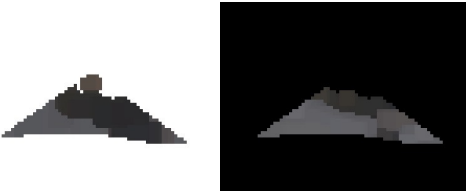
Figure 4. In (a), the image is shrunk to a width of no more than 150 pixels, while computing the local variance shown in (b). Pixels with low variance and suitable colors for lit and shadow pixels are shown in (c) and (d). Those pixels are dilated in (e) and (f). Local gradient maxima with overlapping dilated lit and shadow pixels from (e) and (f) are tested for ISD suitability in (g): White is a big enough gradient but lit-shadowed is too small; light blue is too neutral; dark blue, magenta, and yellow are off the daylight axis; green passes and is a proposed ISD. Note that all the potential ISDs on the car are rejected, and only the shadow edge has green pixels (the proposed ISDs). The list of proposed ISDs is shown in (h). The dominant value is (0.626 0.588 0.511). Because all 13 proposed normals agreed, the confidence is 0.1192 (a low number of agreeing detected normals leads to low confidence).



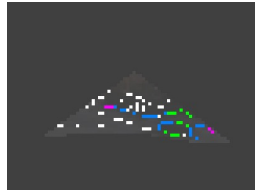
(a) Shrunken Image (b) Local Percent Variance



(c) Potential Shadow Pixels (d) Potential Lit Pixels



(e) Dilated Shadow Pixels (f) Dilated Lit Pixels



(g) Proposed ISDs

0.636674 0.572299 0.516836	0.615775 0.576719 0.536857
0.625451 0.575001 0.527433	0.640388 0.571258 0.513389
0.627111 0.57653 0.52378	0.705571 0.544676 0.453319
0.627111 0.57653 0.52378	0.705571 0.544676 0.453319
0.622473 0.577114 0.528646	0.705571 0.544676 0.453319
0.634764 0.574529 0.516712	0.705571 0.544676 0.453319
0.615775 0.576719 0.536857	0.705571 0.544676 0.453319

(h) List of Proposed ISDs

Figure 5. In (a), the image is shrunk to a width of no more than 150 pixels, while computing the local variance shown in (b). Pixels with low variance and suitable colors for lit and shadow pixels are shown in (c) and (d). Those pixels are dilated in (e) and (f). Local gradient maxima with overlapping dilated lit and shadow pixels from (e) and (f) are tested for ISD suitability in (g): White is a big enough gradient but lit-shadowed is too small; light blue is too neutral; dark blue, magenta, and yellow are off the daylight axis; green passes and is a proposed ISD. The list of proposed ISDs is shown in (h). The dominant value is (0.627 0.575 0.525). Only 9/13 normals agree (the last four are different and are spurious detections from the storm sewer opening). This produces a confidence of 0, so the Kalman filter is not updated.

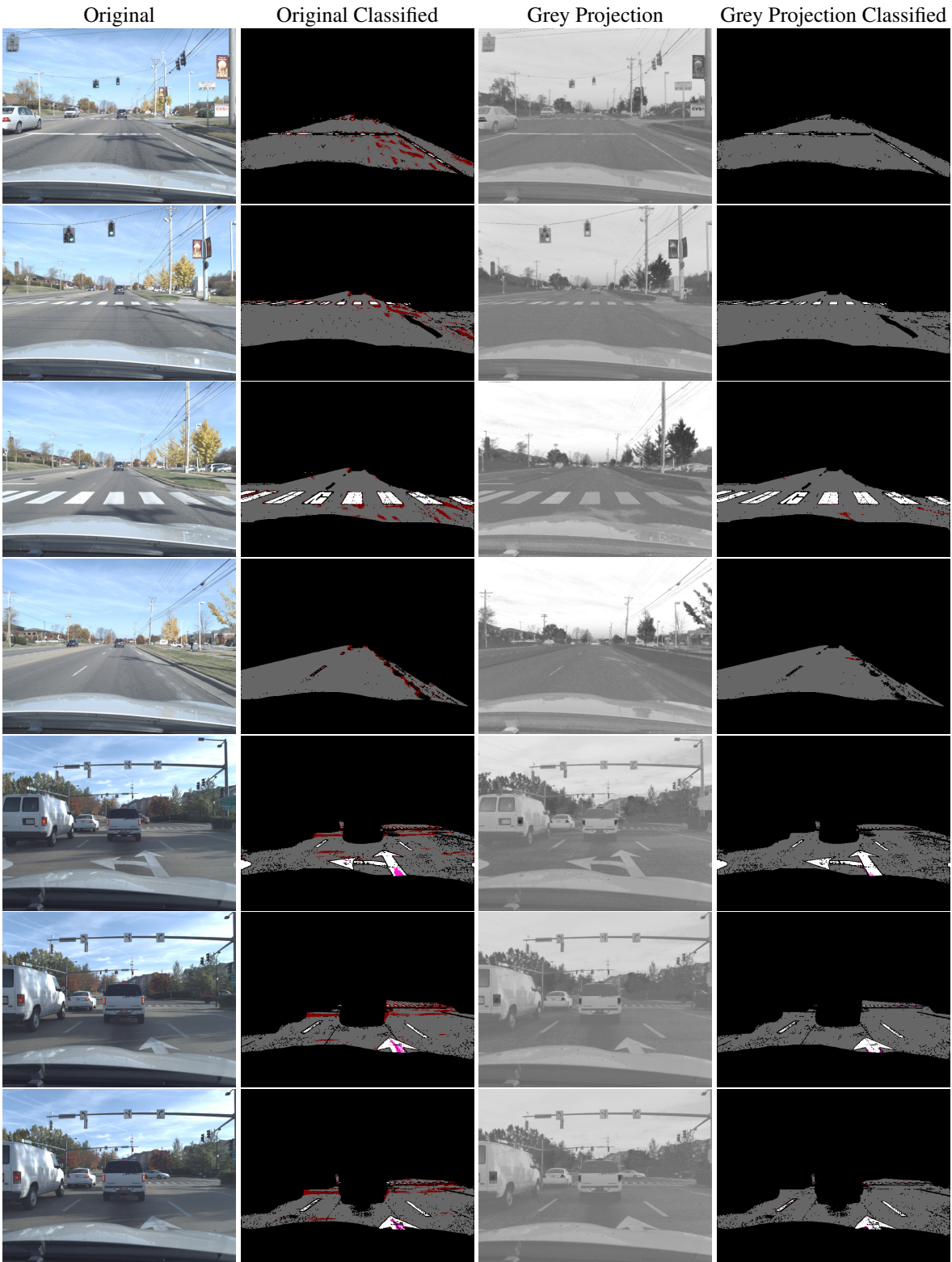


Figure 6. Random Forest test data and results. The classified images are shown at 90% recall across the test set, with correctly classified road pixels shown in grey, correctly classified white paint shown in white, road misclassified as white paint shown in red, and white paint misclassified as road shown in magenta.

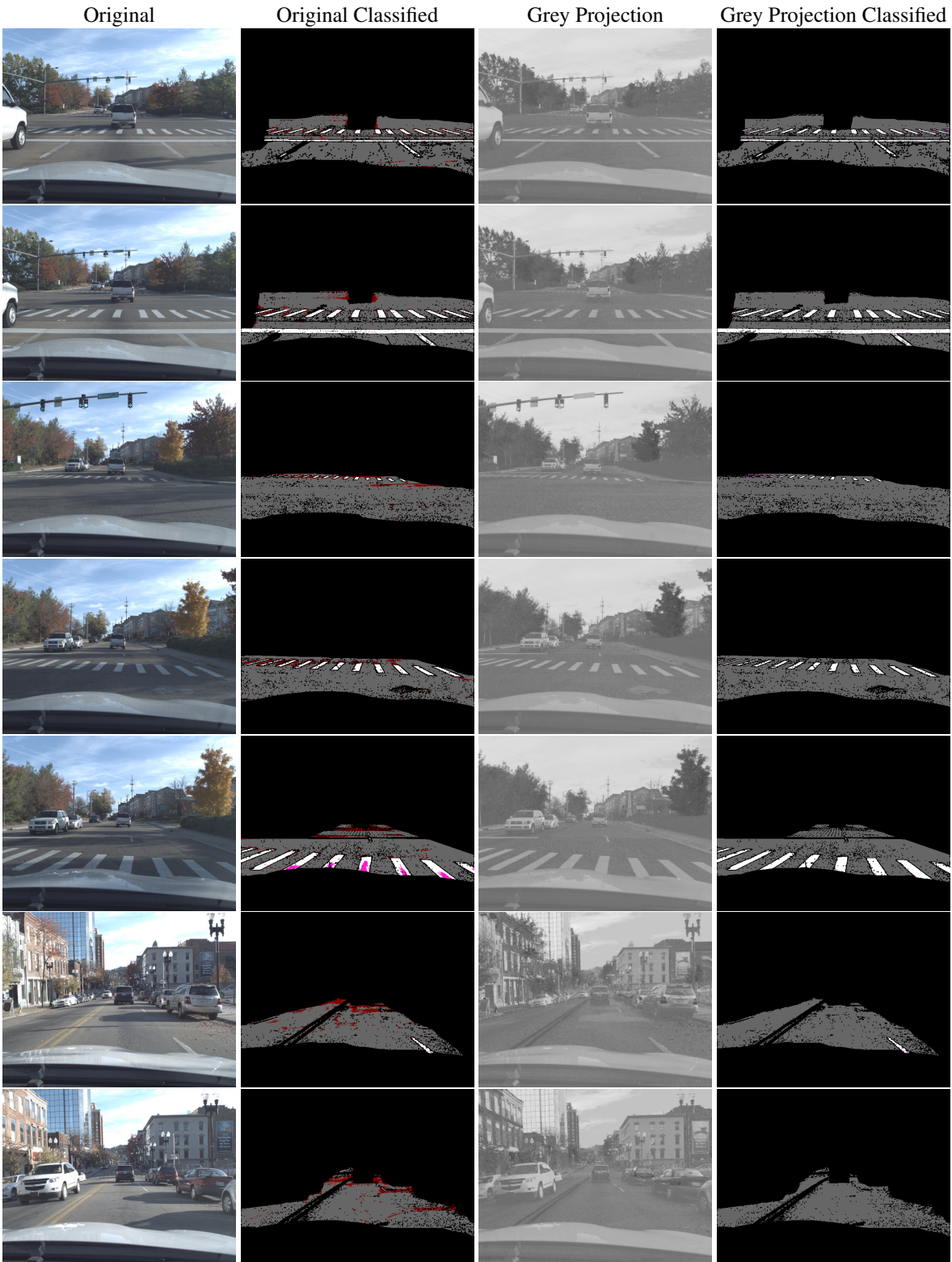


Figure 7. Random Forest test data and results. The classified images are shown at 90% recall across the test set, with correctly classified road pixels shown in grey, correctly classified white paint shown in white, road misclassified as white paint shown in red, and white paint misclassified as road shown in magenta.

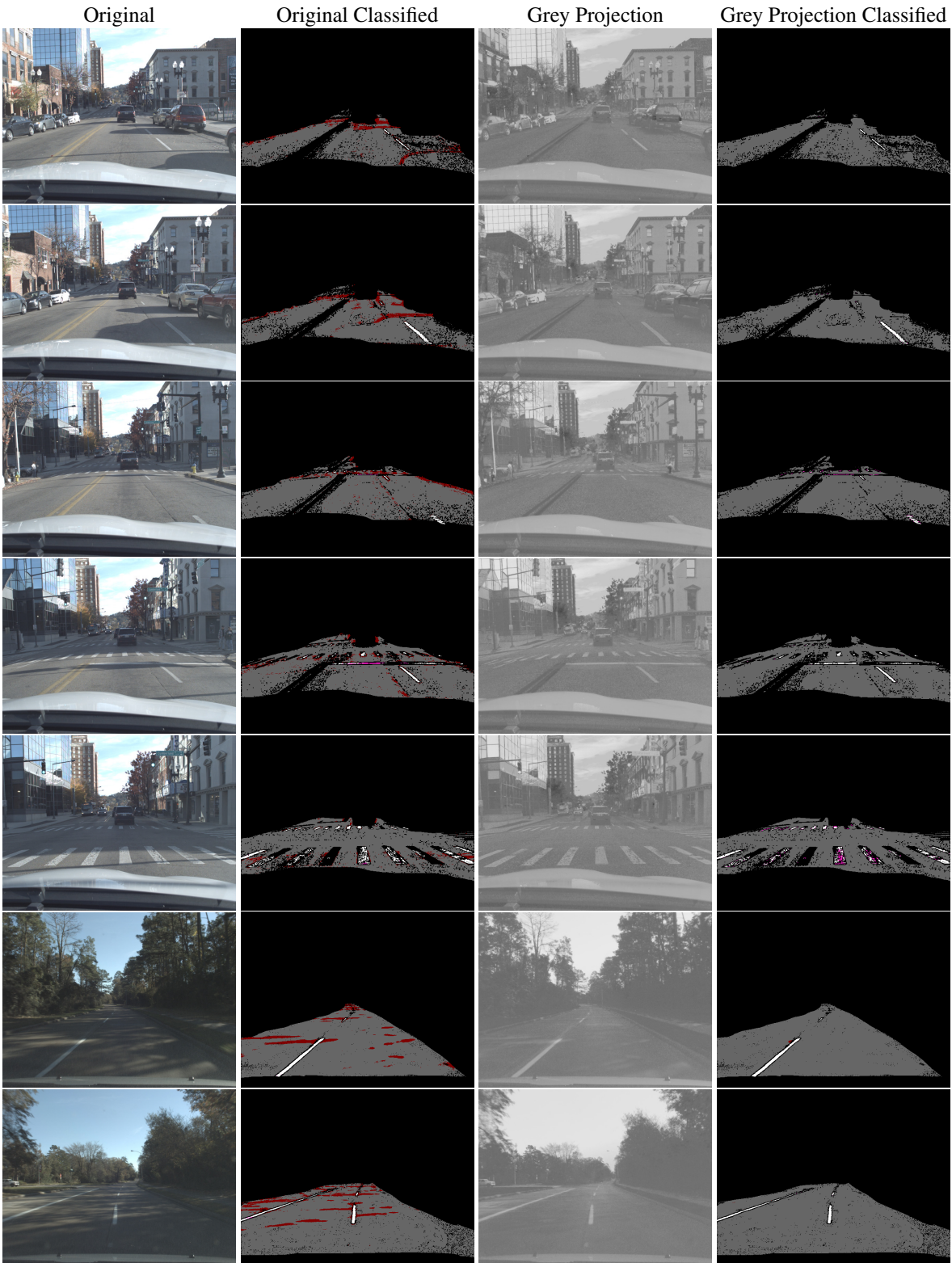


Figure 8. Random Forest test data and results. The classified images are shown at 90% recall across the test set, with correctly classified road pixels shown in grey, correctly classified white paint shown in white, road misclassified as white paint shown in red, and white paint misclassified as road shown in magenta.

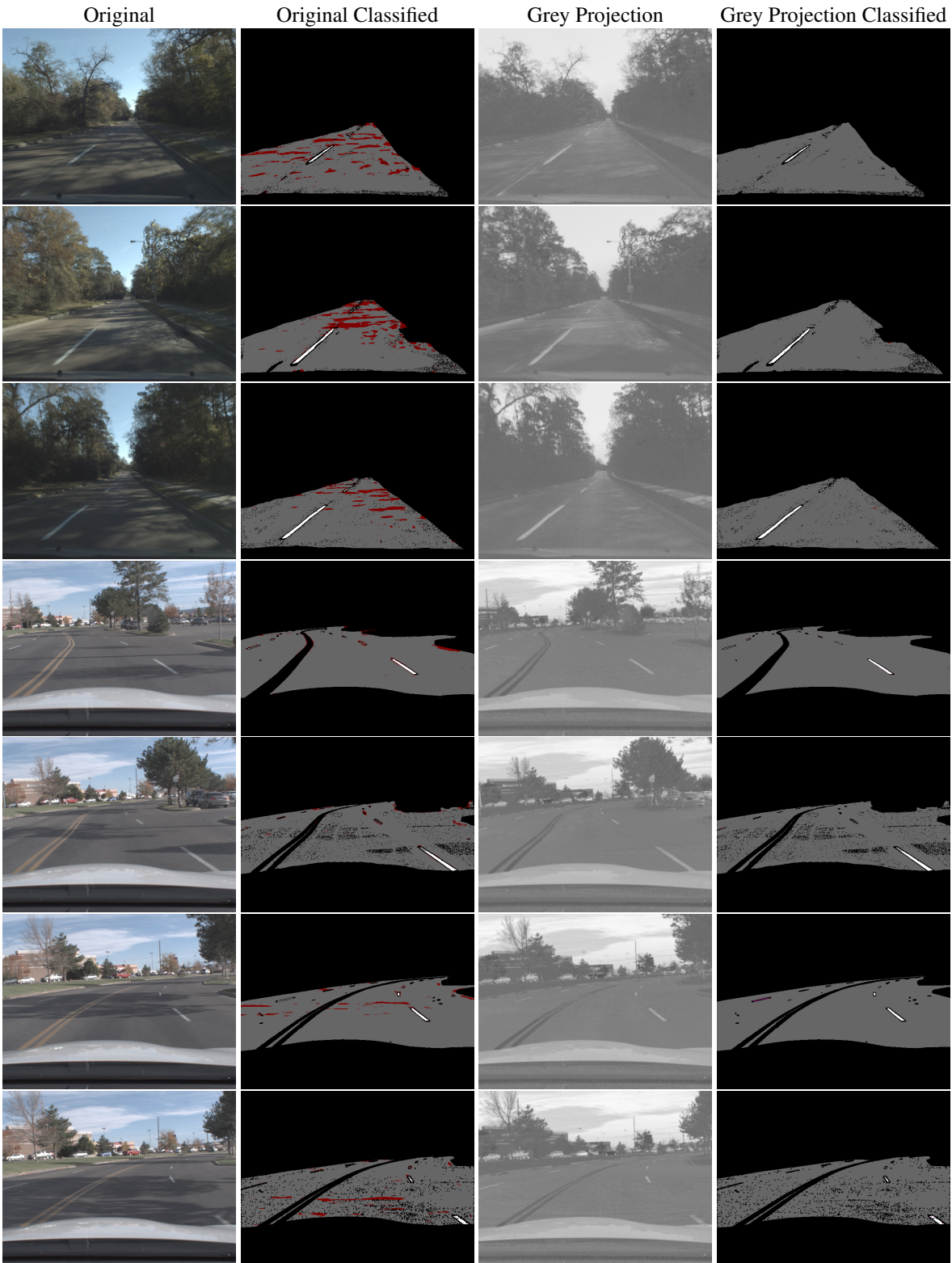


Figure 9. Random Forest test data and results. The classified images are shown at 90% recall across the test set, with correctly classified road pixels shown in grey, correctly classified white paint shown in white, road misclassified as white paint shown in red, and white paint misclassified as road shown in magenta.

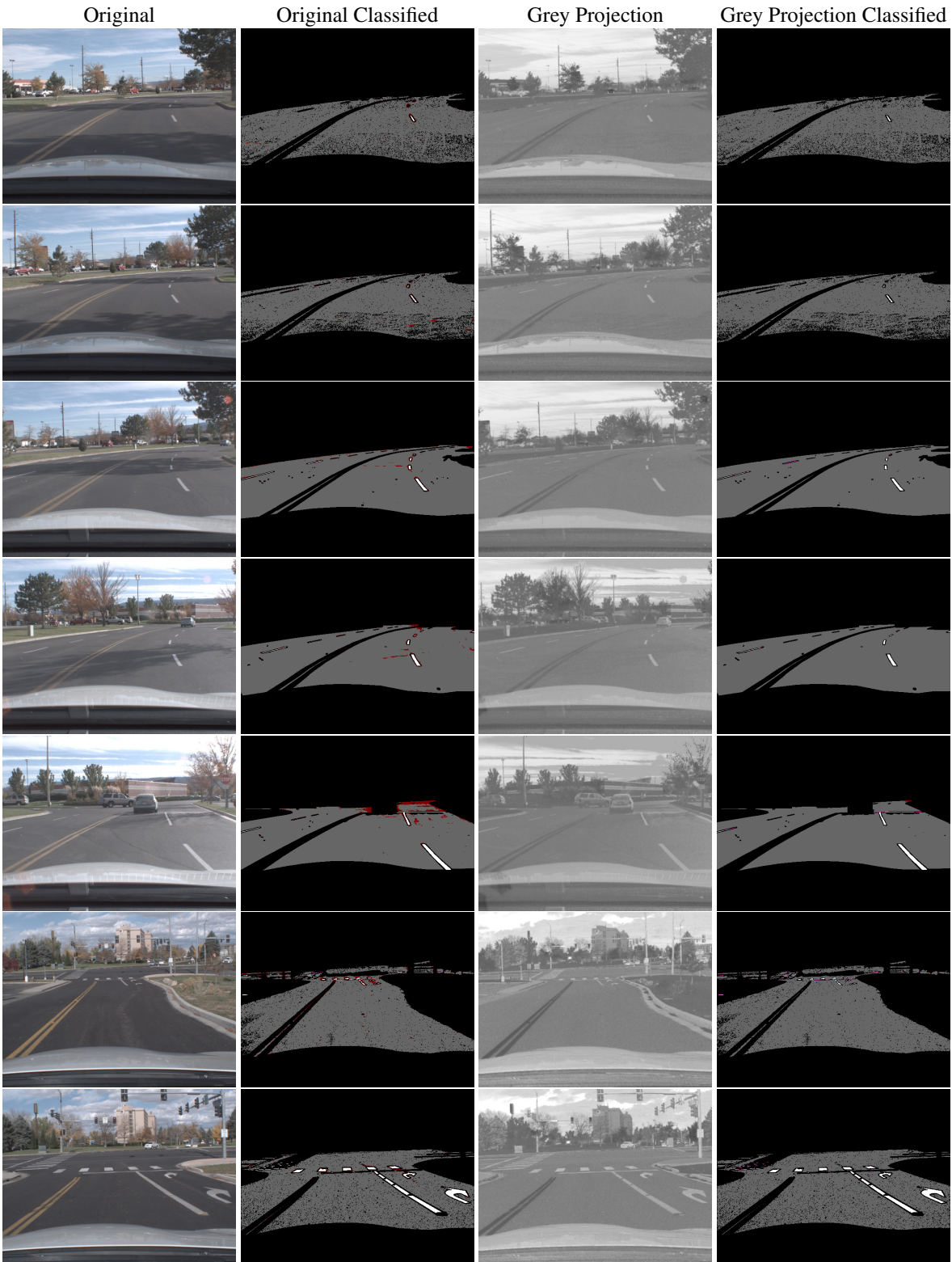


Figure 10. Random Forest test data and results. The classified images are shown at 90% recall across the test set, with correctly classified road pixels shown in grey, correctly classified white paint shown in white, road misclassified as white paint shown in red, and white paint misclassified as road shown in magenta.

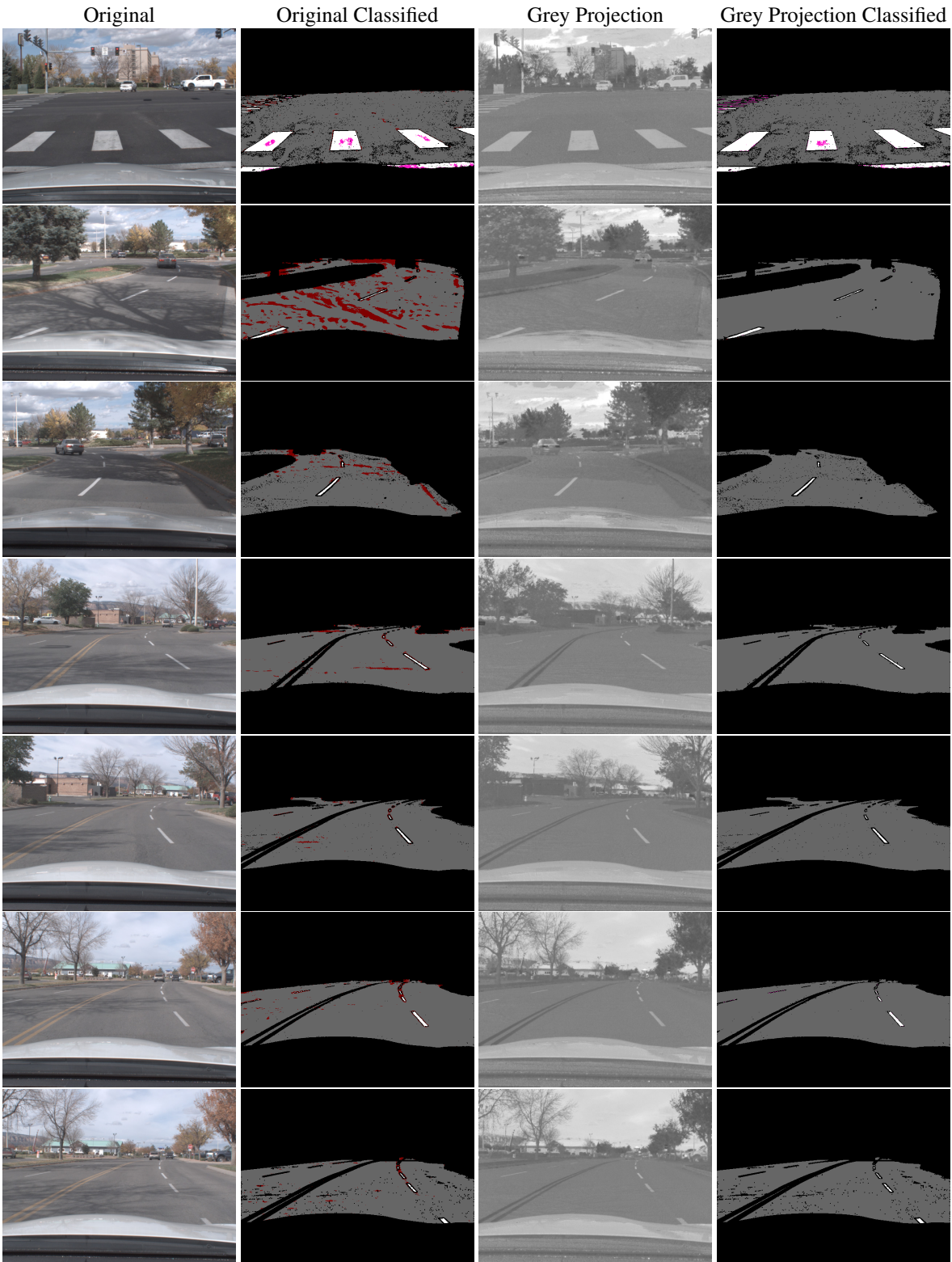


Figure 11. Random Forest test data and results. The classified images are shown at 90% recall across the test set, with correctly classified road pixels shown in grey, correctly classified white paint shown in white, road misclassified as white paint shown in red, and white paint misclassified as road shown in magenta.

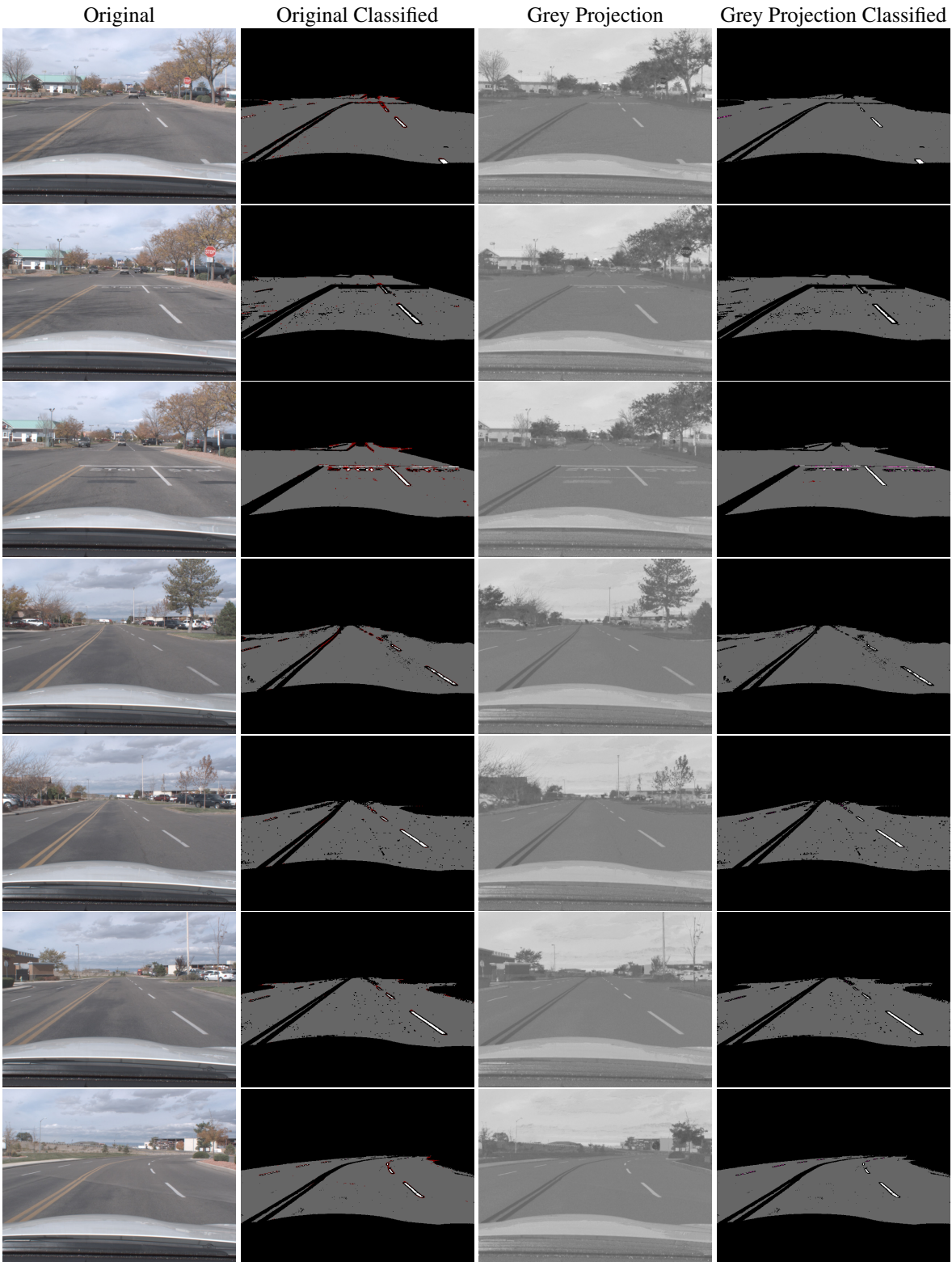


Figure 12. Random Forest test data and results. The classified images are shown at 90% recall across the test set, with correctly classified road pixels shown in grey, correctly classified white paint shown in white, road misclassified as white paint shown in red, and white paint misclassified as road shown in magenta.

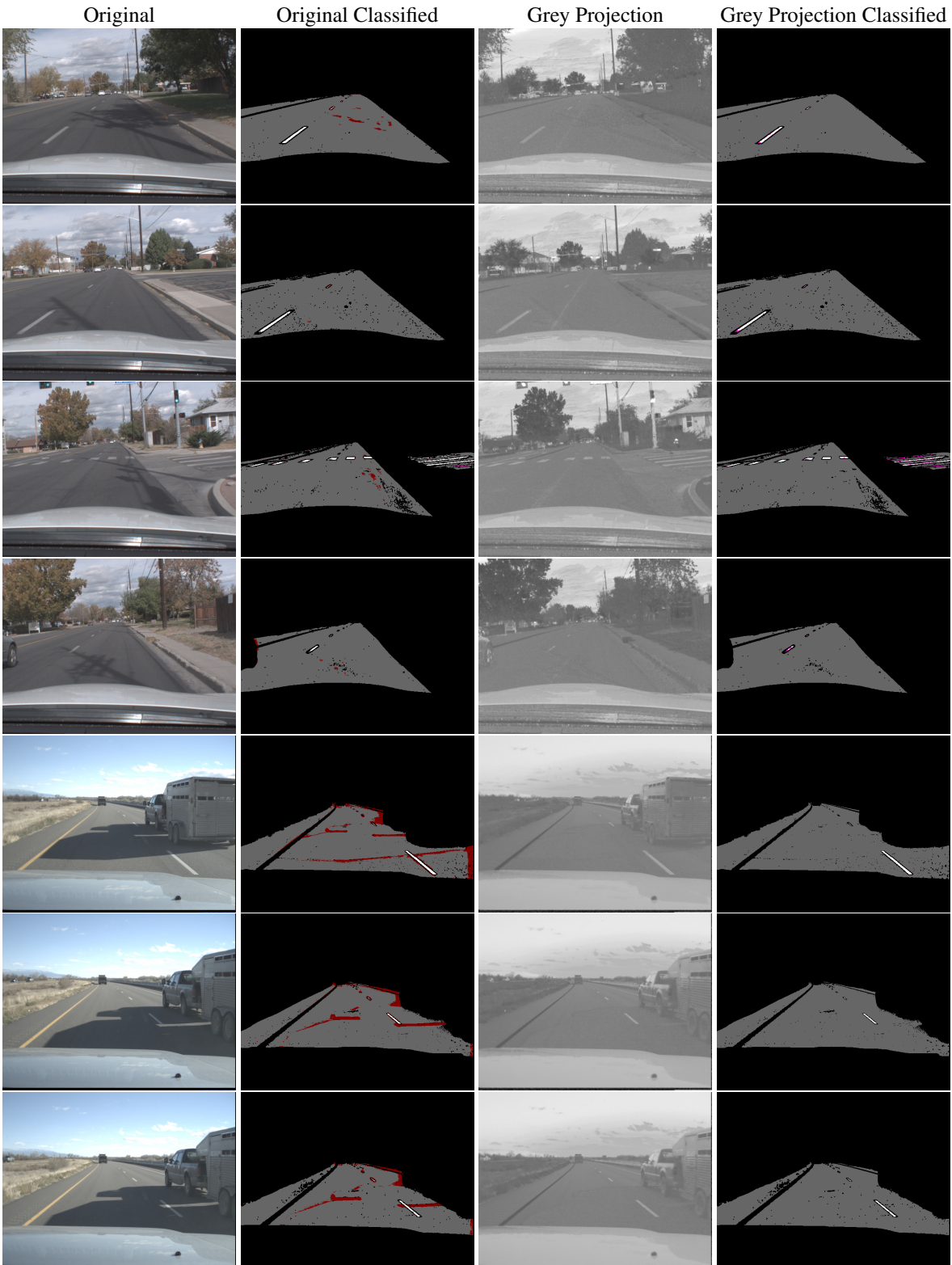


Figure 13. Random Forest test data and results. The classified images are shown at 90% recall across the test set, with correctly classified road pixels shown in grey, correctly classified white paint shown in white, road misclassified as white paint shown in red, and white paint misclassified as road shown in magenta.

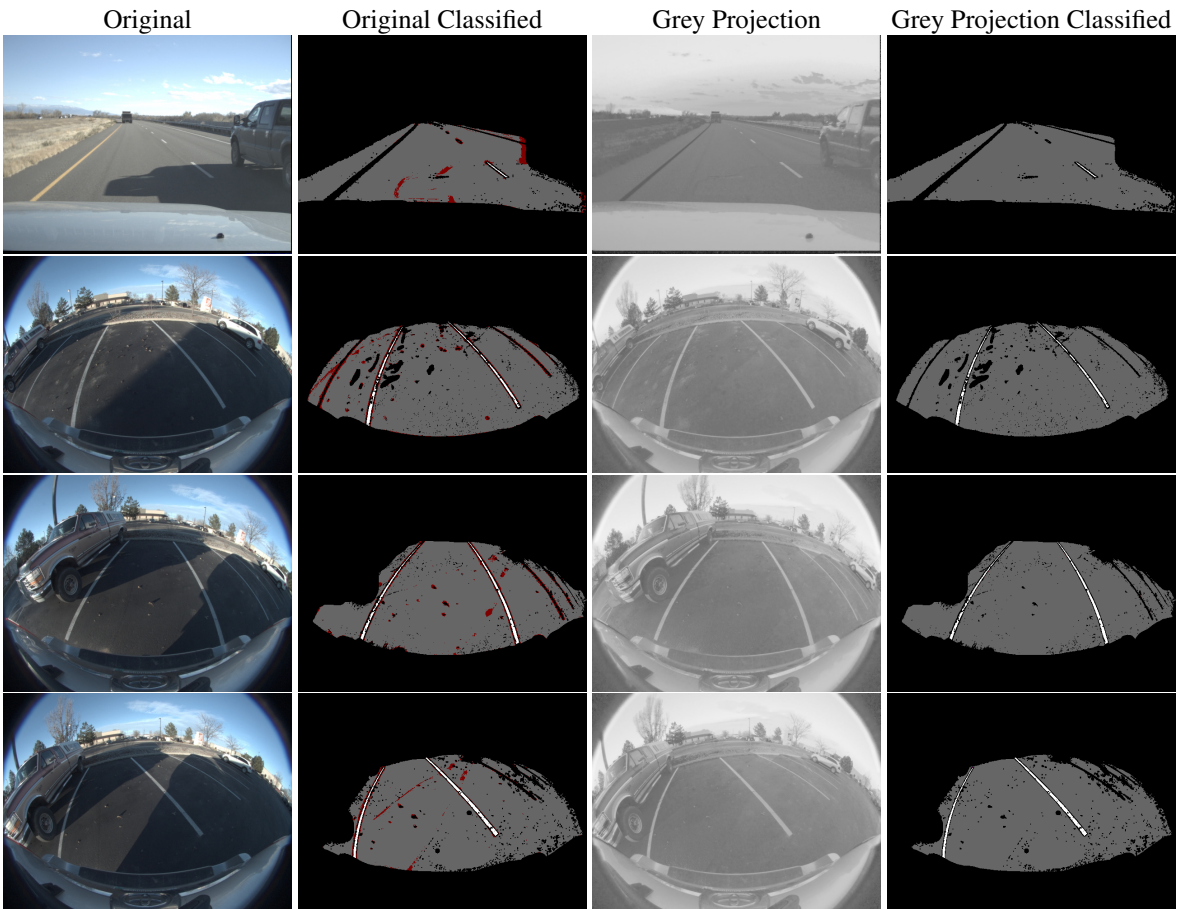


Figure 14. Random Forest test data and results. The classified images are shown at 90% recall across the test set, with correctly classified road pixels shown in grey, correctly classified white paint shown in white, road misclassified as white paint shown in red, and white paint misclassified as road shown in magenta.