Automated Replaced Slab Identification in Jointed Concrete Pavements Using Deep Learning to Improve Pavement Management

Mahla Ardebili Pour, M.S. (Expected Graduation Date: Summer 2026)
Advisors: Somayeh Nassiri; Jeremy Lea

UCPRC UNIVERSITY of CALIFORNIA PAVEMENT RESEARCH CENTER | Davis Berkeley

UC DAVIS UNIVERSITY OF CALIFORNIA

RPUG Road Profile Users' Group

Topic

Agencies need up-to-date records of pavement repairs for asset management and planning. Currently the identification of replaced Jointed Plain Concrete Pavement (JPCP) slabs (Figure 1) is manual and inconsistent. In this work we aim to automatically detect replaced slabs from high-resolution 3D surface images and deep learning. In this way we have faster and more consistent repair databases for planning and budgeting.

Figure 1. JPCP slabs, Caltrans [1]

Background

- Automated vehicle-based sensing and 3D imaging enable fast, consistent collection of detailed pavement surface data at highway speed.
- Prior Machine learning (ML) / Deep Learning (DL) work focuses on surface-level distress detection, such as cracking and potholes (using YOLO (You Only Look Once) model). Replaced-slab identification is largely unstudied [2].
- We developed a sequence-aware CNN-GRU (Convolutional Neural Network-Gated Recurrent Unit) model that extracts features from each slab image and learns patterns across adjacent slabs. This approach is still rarely used for replaced-slab identification [3].

Method

- Dataset: 372,805 labeled slabs from Caltrans 3D pavement imagery. Figure 2(a) shows the 3D imaging method.
- Preprocessing: full-width bottom crop to 400 × 1536 pixels (Figure 2(b)).
- Inputs: slab image + engineered green-channel features (Intensity histogram, LBP (local binary pattern) histogram)
- Model: Figure 3 summarizes the pipeline. 3D slab images are collected, cropped, and normalized. A CNN converts each slab image into a set of learned features; and a GRU uses adjacent-slab context to classify each slab as replaced or not replaced.

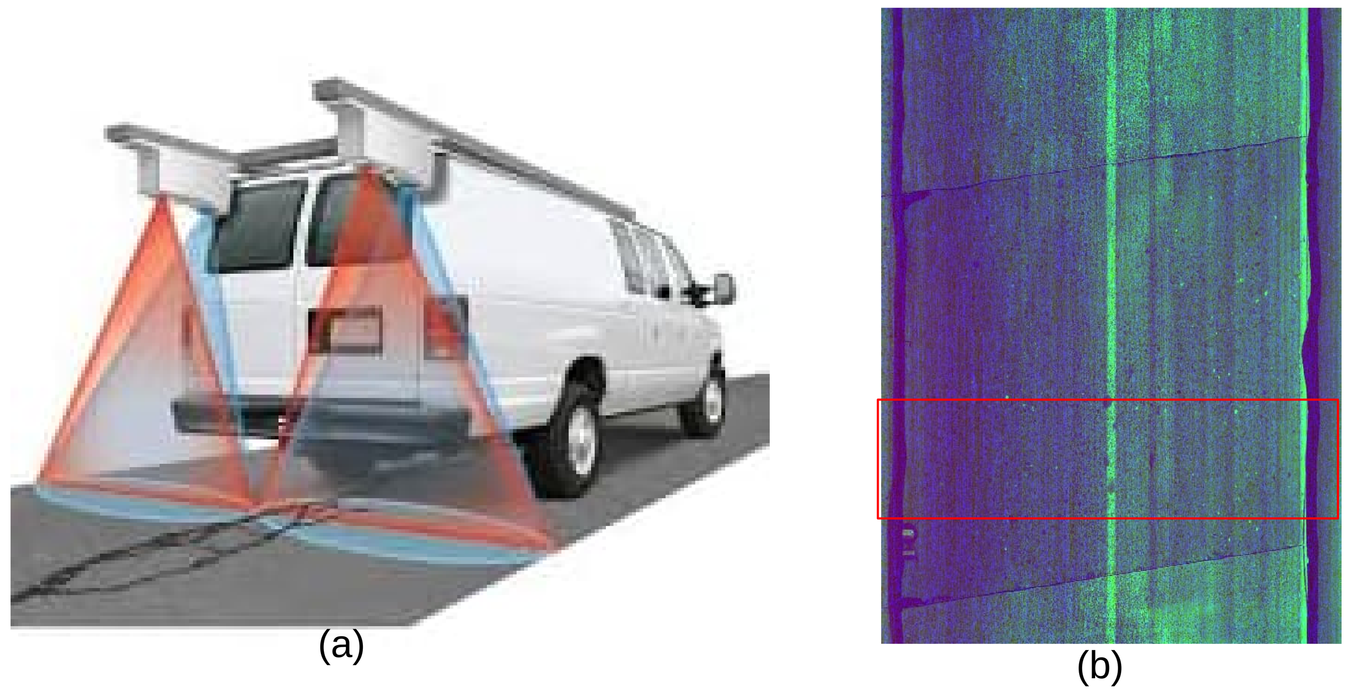

Figure 2.(a) Vehicle-based 3D pavement imaging (Vavrik & Stefanski, RPUG Webinar)[4] (b) JPCP slab image, and the crop box

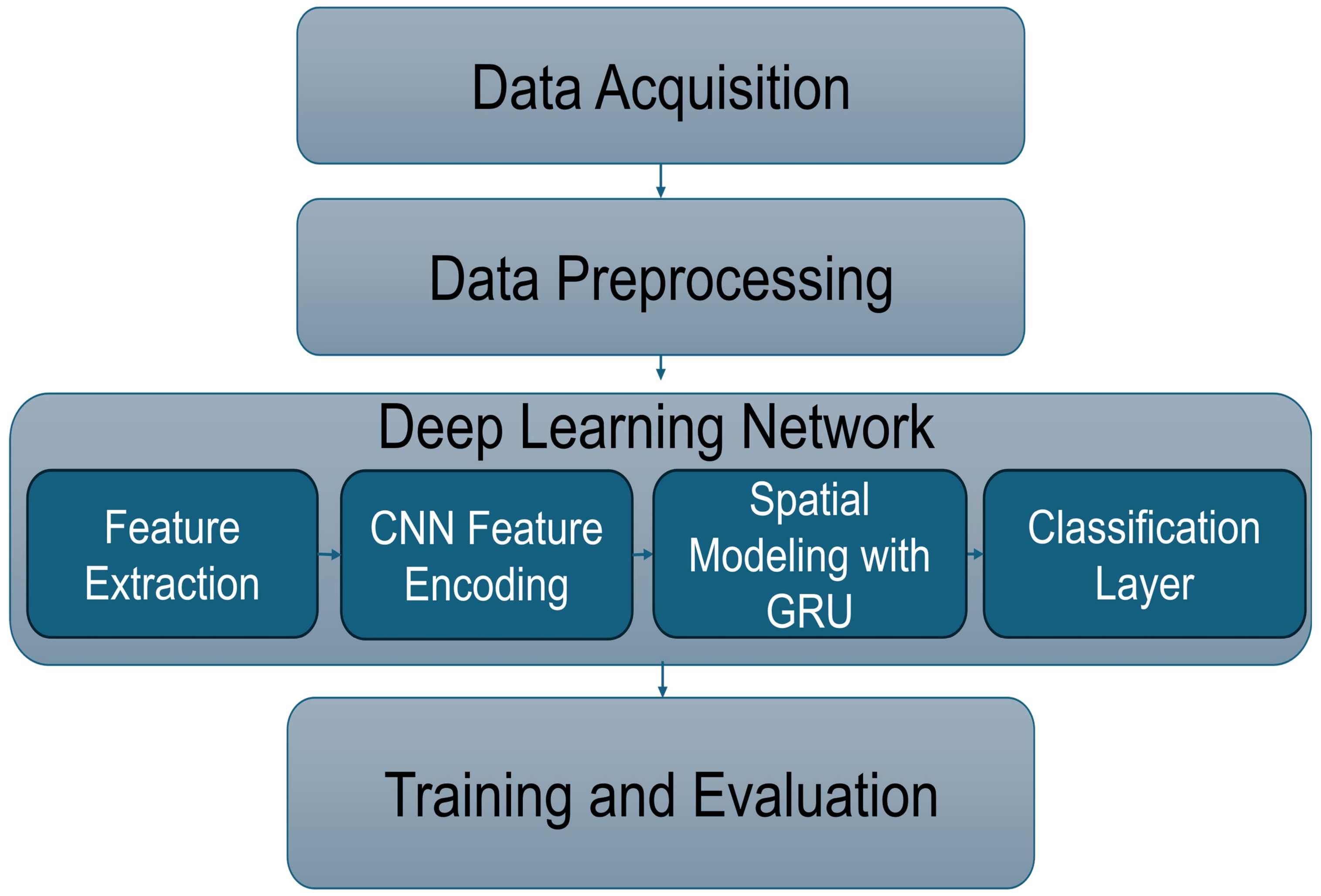

Figure 3. Workflow of this research

Results

- On the test set the model achieved 96% accuracy.
- Figure 4 shows the test confusion matrix, which summarizes correct and incorrect predictions as true positive, true negative, false positive, and false negative (TP/TN/FP/FN). Figure 5 shows some examples from each category. Most errors occur near ambiguous boundaries.

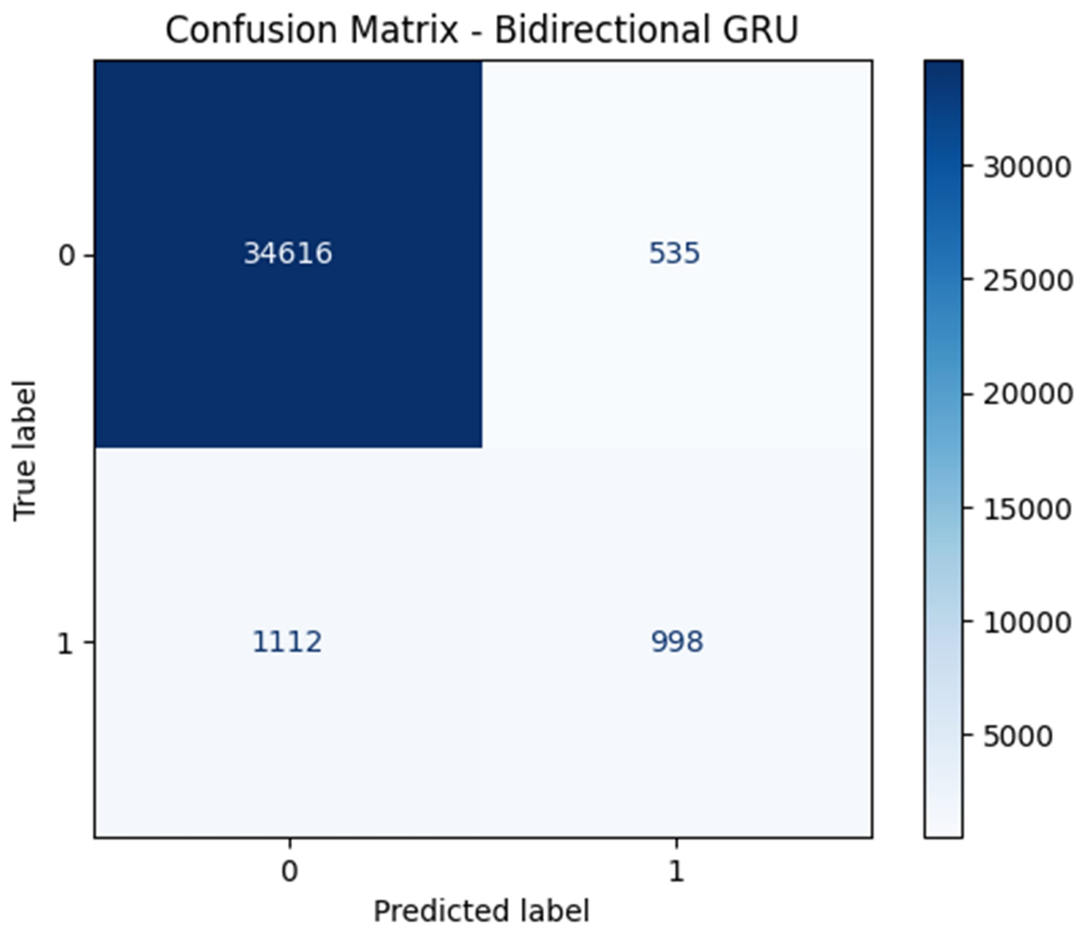

Figure 4. Confusion matrix

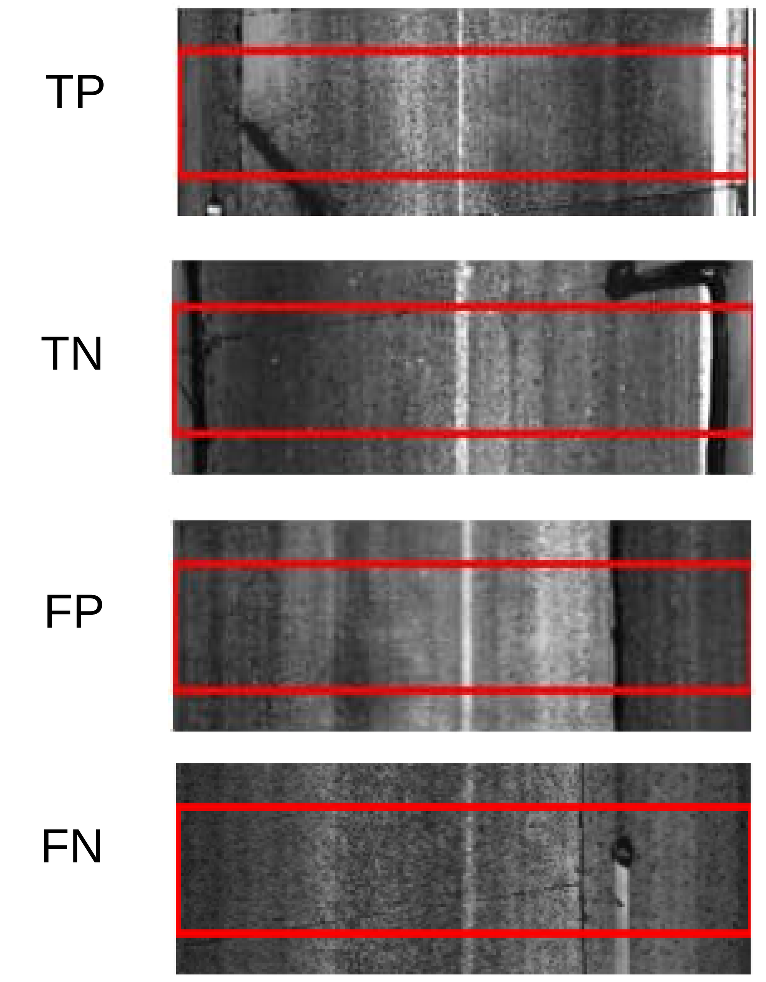

Figure 5. Results from confusion matrix

Recommended Future Work

- Integrate outputs with LRS (Linear Referencing System) / GIS (Geographic Information System) so agencies (e.g., Caltrans) can map predictions to route, lane, and postmile for direct database updates.
- Use a confidence threshold to flag uncertain slabs for review. Agencies only check the uncertain cases, so it saves time and reduces errors.

References

[1] Caltrans Division of Maintenance (accessed Apr. 2026).
[2] Lei, X. et al. IEEE Access 8, 76163–76172 (2020). doi:10.1109/ACCESS.2020.2989028.
[3] Tsai, Y. (James) et al. Caltrans unpublished report (2023).
[4] Vavrik, B., Stefanski, J. RPUG webinar (2020).

Acknowledgements

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