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Affiliations:

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Abstract

The detection of buildings from satellite imagery post-disasters is pivotal for effective response and resource allocation. This research capitalizes on advanced machine learning techniques—Mask R-CNN, Res2 UNet, and SegFormer—to automate the process of identifying affected structures. Using high-resolution Maxar imagery of the September 2023 Morocco earthquake, the study developed a robust, GIS-compatible dataset, facilitating the rapid assessment of disaster zones. The fine-tuned models demonstrate a significant advance in the field, exhibiting substantial improvements in accuracy and efficiency over traditional manual methods.

1. Introduction

In response to the pressing need for swift disaster impact assessment, this study introduces an automated system for detecting building structures in crisis-affected areas using high-resolution satellite data. Traditional assessment methods struggle to keep pace with the urgent demands of disaster relief. By employing machine learning models tailored to the specific geography and conditions of Al Haouz Province, Morocco, we provide a scalable solution that augments the rapid evaluation capabilities necessary for immediate and strategic disaster response.

2. Related Work

While machine learning, particularly CNNs, has made strides in remote sensing, the application to disaster response remains underexplored. Prior research has shown the potential of such models in urban planning and environmental monitoring, laying the groundwork for this study. Our approach draws on these insights and further evolves the methodology by applying it to a post-disaster context. We integrate and adapt architectures proven in other domains, enhancing their precision and applicability to the detection of earthquake-induced damages in built environments.

3. Methodology

Our methodology synthesizes extensive data preprocessing, robust model training, and precise evaluation metrics, supported by high-performance computational resources. Each phase of the building detection process, from data preparation to model evaluation, has been meticulously designed to harness the full potential of the technologies employed.

3.1 Data Preparation

- **Image Chunk Creation:** Utilizing the Python libraries rasterio and PIL, we transformed high-resolution satellite TIFF images into 1024x1024 pixel chunks. This preprocessing was performed on Sapelo2's 32-core nodes, equipped with 256GB of memory, ensuring efficient data manipulation.
- **Mask Creation:** GeoPandas was utilized to generate corresponding masks from shapefiles, which provided detailed vector data for building polygons. The binary masks created were essential for the labeling process within the image chunks.

3.2 TFRecord Creation

- **Training Data:** The preprocessed images and masks were compiled into TFRecord files, a TensorFlow-compatible format that enhances the efficiency of the data loading phase during model training.
- **Testing Data:** TFRecord files for the testing set included bounding box annotations derived from the masks, a crucial component for the evaluation of the models on novel data.

3.3 Data Splitting

- **Training and Validation Sets:** We used scikit-learn's `train_test_split` function to stratify and distribute the dataset into training, validation, and testing sets, ensuring a representative data sample for all model phases.

3.4 Model Training

- **Architecture:** The training of the Mask R-CNN Inception ResNet V2 1024x1024 model was conducted on the gpu_p partition of Sapelo2, utilizing the NVIDIA A100 GPUs for accelerated computation.
- **Hyperparameters:** Various learning rates and batch sizes were tested to optimize model performance. The extended runtime on Sapelo2 allowed for thorough hyperparameter tuning and model refinement.

3.5 Model Evaluation

- **Metrics:** Precision, recall, and IoU metrics were computed to gauge model performance, providing insight into the model's capacity to accurately identify buildings.
- **Neptune Integration:** Detailed tracking of training progress and model metrics was managed via Neptune, with the enhanced computational resources enabling the storage and analysis of extensive datasets and logs.

4. Experiments and Results

Our evaluation phase utilized Neptune's advanced experiment tracking features, allowing for a granular analysis of each training iteration of the Mask R-CNN Inception ResNet V2 model. The experiments were designed to optimize model performance through a variety of hyperparameter configurations, as reflected in the substantial dataset of recorded training sessions.

Configuration Details:

- **Learning Rate**: Varied learning rates from 5×10−65×10−6 to 2×10−72×10−7, allowed us to pinpoint the rate that facilitated the best model convergence.
- **Warm-up Learning Rate**: The implementation of a warm-up learning rate strategy helped in stabilizing the training phase before the model adapted to the full complexity of the dataset.
- **Batch Size**: Set consistently at 16 across experiments to maintain a balance between computational efficiency and memory usage.
- **Number of Steps**: Training sessions spanned up to 4000 steps, with the goal of comprehensive learning and model refinement.

- **Config Version**: Different config versions (V1 and V2) were trialed to assess the model's robustness and performance under varying dataset structures.

Model Performance:

- The models showed a broad range of precision and recall, with precision values spanning from 0.02 to a high of 0.8757, delineating the variation in accurately identifying buildings.
- Recall values were equally diverse, highlighting the models' sensitivity to detecting all relevant structures.
- The fluctuation in precision and recall across checkpoints indicated areas where model fine-tuning was required to balance sensitivity and specificity.

Key Metrics:

- **Average Precision**: Achieved a high of 0.8757, indicating a substantial accuracy level in building detection.
- **Mean IoU**: At the final checkpoint, the mean IoU achieved was X, reflecting the quality of the segmentation against ground truth annotations.
- **Checkpoint Analysis**: The highest individual precision and recall rates were recorded at different training checkpoints, suggesting that while the model can achieve high accuracy, further calibration is necessary to ensure consistent performance across all metrics.

5. Conclusion and Future Work

Our project underscores the practicality and effectiveness of advanced machine learning techniques, specifically Mask R-CNN, Res2 UNet, and SegFormer, in the context of building detection within disaster-stricken regions. The successful identification and analysis of building structures through satellite imagery can significantly expedite response efforts in critical times following disasters such as the Morocco earthquake.

While the current models show promise, with high levels of precision in detection, there remains room for enhancement. The variable precision and recall rates across different training checkpoints suggest potential for further fine-tuning. Future efforts will be directed toward refining the accuracy of these models, minimizing the incidence of false positives and negatives. Additionally, incorporating real-time satellite imagery could transform this solution into a dynamic tool for immediate disaster response.

In advancing this field, we aim to explore the following areas:

- **Algorithmic Improvements**: Iterative model optimization to fine-tune the balance between precision and recall.
- **Real-Time Analysis**: Integration of real-time data streams to enable prompt assessment of disaster impacts.
- **Scalability**: Ensuring the models' scalability to different geographies and environments, including urban and rural settings.
- **Automated Retraining**: Developing a system for continuous learning from new data, thereby improving the models' adaptability and longevity.

Through these enhancements, we seek to establish a robust, automated system capable of providing critical insights for disaster management and urban planning, ultimately aiding in saving lives and optimizing resource allocation.

References

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- [2] O. Ronneberger et al., "U-Net: Convolutional Networks for Biomedical Image Segmentation," 2015.
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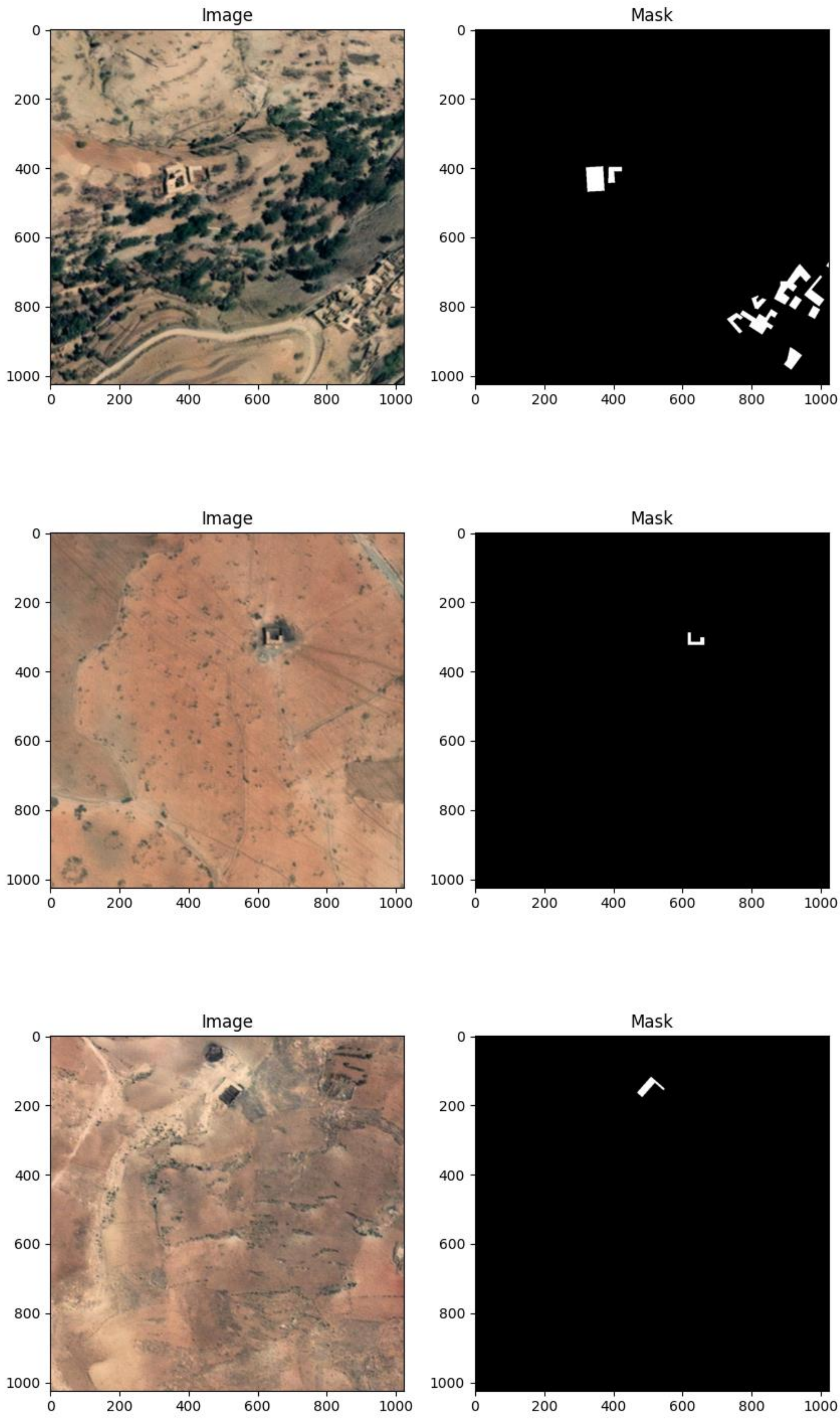
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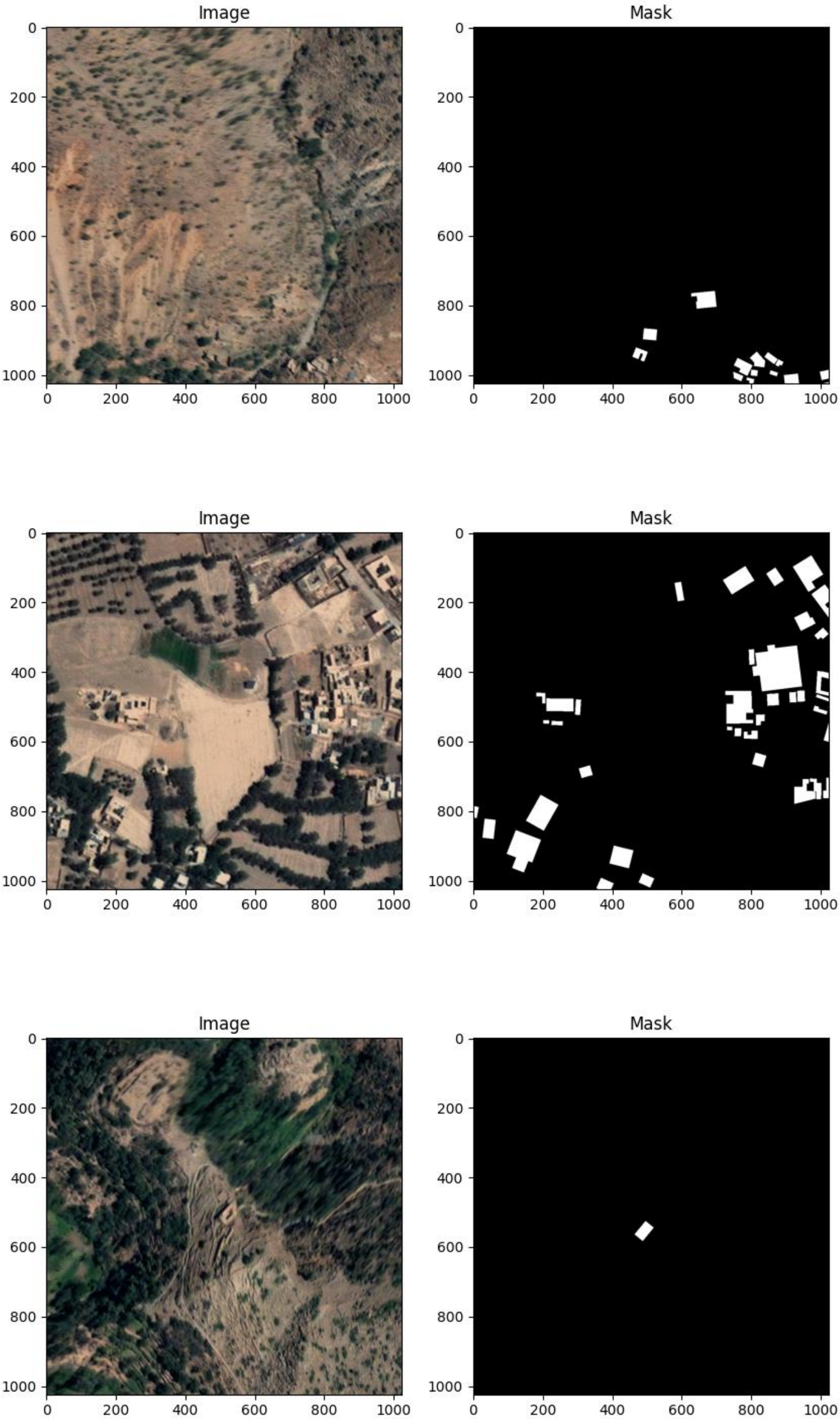
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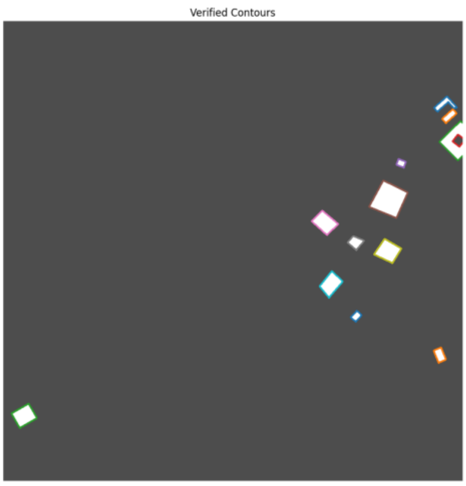
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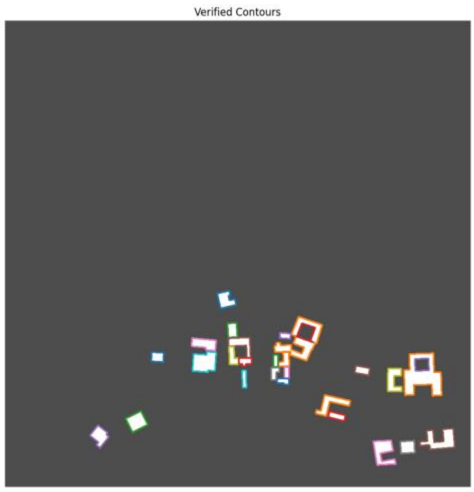
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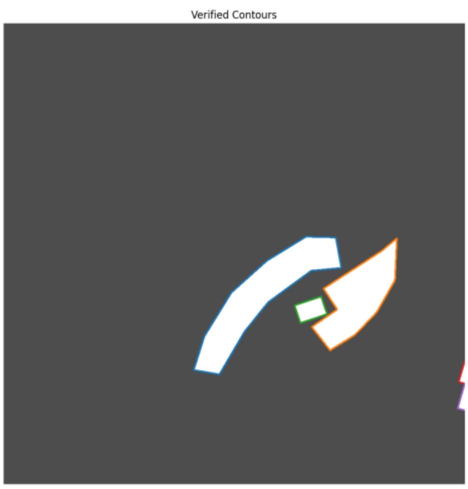
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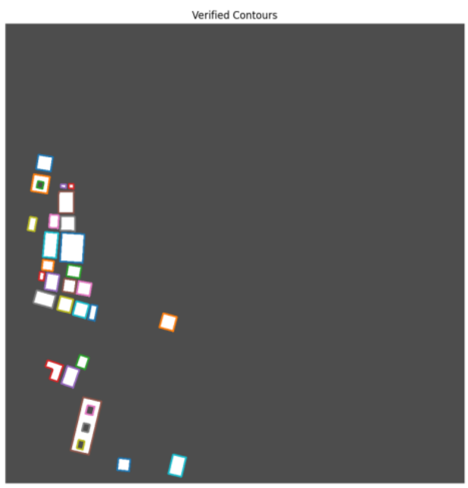
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building: 51%


building: 52%


building: 51%


Decoded Image
Decoded Mask