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AI-Based Building Damage Assessment in Post-War Sudan Using Deep Learning and Remote Sensing

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1. Background

This project lies within the intersection of Artificial Intelligence (AI) and Disaster Management, focusing on the use of intelligent systems to assess and support post-conflict reconstruction in Sudan.

AI-based disaster assessment leverages computer vision and deep learning techniques to automatically analyze satellite and aerial imagery for damage detection — a process that significantly improves accuracy and reduces the time required compared to traditional manual assessments (Li et al., 2023).

The proposed system will integrate Convolutional Neural Networks (CNNs) within a user-friendly web platform to evaluate the extent of infrastructure damage and visualize the results through interactive maps.

This aligns with global efforts in smart reconstruction and digital resilience, similar to projects developed by UN-Habitat (2022) and the Build Change Foundation (2021), but will be tailored to Sudan's post-war context and technological landscape.

2. Project Significance

The significance of this project lies in offering a scalable and intelligent digital tool to support evidence-based reconstruction planning in Sudan.

It aims to:

- Provide an automated, AI-driven solution for damage detection, enhancing speed, objectivity, and cost-efficiency.
- Contribute to academic and applied research in AI for disaster recovery, bridging the gap between theory and real-world implementation.
- Support governmental and humanitarian organizations in prioritizing reconstruction efforts based on accurate data.
- Promote transparency and equitable resource distribution in the national rebuilding process.

From a theoretical perspective, the project extends the use of deep learning in post-disaster assessment frameworks, while practically, it demonstrates how AI-powered platforms can aid infrastructure rehabilitation in data-scarce regions.

3. Previous studies

Study 1:

Title / Researchers / Year

Damage Detection from Aerial Images via Convolutional Neural Networks — by Aito Fujita, Ken Sakurada, Tomoyuki Imaizumi, Riho Ito, Shuhei Hikosaka, and Ryosuke Nakamura, 2017 (Advanced Industrial Science and Technology, Japan; Nagoya University).

Objectives

The study aimed to develop and evaluate a CNN-based framework for detecting washed-away buildings after the 2011 Great East Japan earthquake and tsunami, using pre- and post-event aerial imagery. It sought to determine the most effective CNN configurations and input settings for automated large-scale damage detection (Fujita et al., 2017).

Dataset Size

A new labeled dataset named ABCD (AIST Building Change Detection) was created, containing:

- 10,777 pairs of fixed-scale image patches (4,253 washed-away).
- 11,394 pairs of size-adaptive and resized patches (4,546 washed-away). These pairs were derived from 66 km² of tsunami-affected areas and 220,000 surveyed buildings (Fujita et al., 2017).

Methodology (Tools & Techniques)

- Constructed and trained various CNN architectures:
    - 6-channel CNN (combining pre- and post-tsunami images).
    - Siamese CNN (two-branch network with unshared weights).

- Tested multiple input scale strategies: fixed-scale, resized, ensemble, and multi-scale (central-surround).
- Used 5-fold cross validation with Bayesian optimization for hyperparameters.
- Implemented and trained all models using Caffe deep learning framework with SGD optimization.

Results

- The proposed system achieved 94–96% classification accuracy across all configurations.
- The Siamese CNN slightly outperformed the 6-channel network.
- Combining models with different input scales (ensemble) consistently improved accuracy (Fujita et al., 2017).

Opinion (Findings + Limitations)

- **Strengths:**
    - High detection accuracy and robust performance across input scenarios.
    - Introduced a valuable labeled aerial dataset (ABCD) for post-disaster analysis.
- **Limitations:**
    - Relies on existing building location data rather than detecting buildings automatically.
    - The system performs classification, not full object detection or segmentation.

Study 2:

Title / Researchers / Year

Building Damage Assessment with Deep Learning — by S. May, A. Dupuis, A. Lagrange, F. De Vieilleville, and C. Fernandez-Martin, 2022 (CNES and Agenium Space, France).

Objectives

The study aimed to develop a deep learning–based framework for automatic building damage assessment using satellite imagery collected before and after natural disasters. It sought to compare multiple CNN architectures and assess their performance in detecting buildings and classifying damage levels (May et al., 2022).

Dataset Size

Two main datasets were used:

- xView2 Dataset: Includes six disaster types (earthquake, flood, hurricane, fire, tsunami, volcano) across 11 countries, with both pre- and post-event high-resolution images (0.3–3 m GSD). It contains four damage classes — no damage, minor, major, and destroyed.
- Haiti Dataset: Pleiades satellite images (before and after Hurricane Matthew, October 2016) with 3 damage levels — no damage, damaged, destroyed.

Methodology (Tools & Techniques)

- **Deep Learning Architectures:**
    - UNet, MobileNetV2, SE-ResNet, and EfficientNet for building segmentation.
    - Siamese Networks (shared weights) and binary vs. multiclass segmentation for damage classification.
- **Training setup:**
    - Images resized to 224×224 pixels; batch size 32; 200 epochs.
    - Loss function: Balanced cross-entropy + Dice loss.
    - Optimizer: Stochastic Gradient Descent.
    - Augmentation: flips, rotations, zoom, and brightness adjustments.

Results

- Building Segmentation: UNet–EfficientNet-B5 achieved the highest F1 score = 0.834 (83.4%), outperforming other architectures.

- Damage Classification: UNet–EfficientNet-B0 achieved the best multiclass results with F1-scores of 0.79 (no damage), 0.41 (minor), 0.63 (major), and 0.70 (destroyed).
- Binary vs. Multiclass Models: Merging multiple binary networks did not outperform a single multiclass network.

Opinion (Findings + Limitations)

- **Strengths:**
  - Comprehensive comparison of modern deep learning models (EfficientNet, SE-ResNet, MobileNet).
  - Successful application of Siamese networks for pre-/post-disaster comparison.
  - Achieved strong segmentation and classification results on real satellite data.
- **Limitations:**
  - Difficulty in distinguishing minor vs. major damage classes.
  - Dependent on high-quality pre/post-event imagery and accurate ground truth segmentation.
- **Potential improvement for our project:**

  Combine segmentation and classification into an end-to-end pipeline (e.g., integrating UNet-EfficientNet with object detection frameworks) to improve minor-damage detection and automate per-building analysis.

Study 3:

Title / Researchers / Year

Remote Sensing and Machine Learning for Enhanced Post-Disaster Response: Insights from the 2023 Türkiye–Syria Earthquake — by Mohsen Azimi, Armin Dadras Eslamlou, T.Y. Yang, and Shiping Huang, 2024 (The University of British Columbia; South China University of Technology; National Central University, Taiwan) .

Objectives

The study aimed to investigate how remote sensing data combined with machine learning and deep learning models can improve post-disaster damage assessment and response efficiency, using the 2023 Türkiye–Syria Earthquake as a case study (Azimi et al., 2024).

Dataset Size

The research utilized multi-sensor remote sensing data — including optical, SAR (Synthetic Aperture Radar), and LiDAR imagery — covering extensive earthquake-affected areas in Türkiye and Syria. The datasets incorporated both pre- and post-event satellite imagery for large-scale building damage evaluation.

Methodology (Tools & Techniques)

- Integrated remote sensing techniques (SAR coherence analysis, change detection, optical classification).
- Employed machine learning algorithms (Random Forest, SVM) and deep learning architectures (CNN, UNet) for automated damage mapping.
- Combined multi-temporal and multi-source data to enhance classification accuracy and response timeliness.
- Evaluated performance using accuracy, precision, recall, and F1-score metrics.

Results

- Deep learning models (CNN/UNet) achieved superior performance in identifying collapsed structures compared to traditional ML methods.
- Integration of SAR and optical data improved overall detection accuracy and reduced false positives.
- Demonstrated that combining remote sensing and deep learning enables near–real-time damage mapping and enhances disaster response capacity (Azimi et al., 2024).

Opinion (Findings + Limitations)

- **Strengths:**
  - Comprehensive multi-sensor approach for rapid and accurate post-disaster mapping.
  - Demonstrated the practical advantage of deep learning for large-scale response.
- **Limitations:**
  - Relies heavily on data availability and quality, particularly SAR coverage.
  - The system lacks operational automation for instant deployment.

4. Problem Statement

Sudan's recent war has caused extensive, undocumented damage to critical infrastructure (buildings, roads, bridges, utilities). Current assessments rely on slow, manual surveys or fragmented satellite/social media data—prone to bias and inefficiency. This creates an information gap that delays humanitarian aid, reconstruction, and decision-making.

Despite proven deep learning and remote sensing success in events like the 2023 Türkiye–Syria earthquake (Azimi et al., 2023), no localized, integrated framework exists for Sudan.

This project fills this gap with an automated AI platform that:

- Detects and quantifies damage from aerial/satellite imagery
- Maps destruction in real time
- Prioritizes recovery using social impact data
- Tracks projects transparently for stakeholders

This enables faster; evidence-based reconstruction tailored to Sudan's context.

5. Research Questions and Hypotheses

This project seeks to explore how deep learning and remote sensing can be effectively applied for infrastructure damage assessment in post-war Sudan. Based on the identified problem, the following research questions (RQs) and hypotheses (Hs) are proposed:

Research Questions (RQs)

1. **RQ1:** How can satellite and aerial imagery be used to automatically detect and classify infrastructure damage in post-war Sudan?
2. **RQ2:** What are the main challenges related to data availability, quality, and coverage for automated damage assessment in Sudanese cities?
3. **RQ3:** How accurately can a deep learning model (e.g., CNN-based framework) identify different levels of infrastructure damage within the selected pilot area?
4. **RQ4:** How can the findings from a small pilot region be scaled up to support national-level reconstruction planning?

Hypotheses (Hs)

- **H1:** Deep learning models (e.g., CNN architectures) can achieve high accuracy in classifying damaged versus undamaged infrastructure using post-war satellite imagery.
- **H2:** The integration of pre- and post-event imagery improves the model’s reliability compared to using post-event data alone.
- **H3:** Model performance can be enhanced through data augmentation and fine-tuning using Sudan-specific imagery.

6. Objectives

General Objective

To develop and implement a deep learning–based framework that automatically detects and assesses infrastructure damage in post-war Sudan using aerial and satellite imagery, thereby supporting evidence-based reconstruction and humanitarian decision-making.

Specific Objectives

1. To collect and preprocess remote sensing data (satellite and aerial images) for selected Sudanese regions affected by the war.

2. To design and train a deep learning model (CNN-based) capable of identifying and classifying infrastructure damage levels (e.g., no damage, partial, or destroyed).

3. To evaluate the model's performance using standard metrics (accuracy, precision, recall, F1-score) on a geographically limited pilot area.

4. To analyze data limitations and contextual challenges specific to Sudan, such as resolution, cloud cover, and availability of pre-war imagery.

5. To propose a scalable workflow for extending the damage assessment system to broader regions across Sudan.

6. To document and validate the findings academically, ensuring the project contributes to the growing field of post-conflict infrastructure monitoring.

7. Methodology / Framework

This project will adopt an applied research methodology integrating remote sensing, deep learning, and geospatial analysis to evaluate post-war infrastructure damage in Sudan. The workflow is designed to ensure that the process can be replicated, validated, and scaled to larger geographic areas.

Step 1: Data Collection and Preparation

- Obtain satellite and aerial imagery (e.g., Sentinel-2, PlanetScope, or Pleiades) covering selected war-affected areas in Sudan.
- Gather pre- and post-conflict imagery, where available, to enable comparative analysis.
- Perform georeferencing, radiometric correction, and image alignment to ensure spatial accuracy.

Step 2: Dataset Construction

- Manually or semi-automatically label sample areas into categories such as no damage, partially damaged, and destroyed.
- Divide the dataset into training, validation, and testing subsets (e.g., 70/15/15 split).
- Apply data augmentation (rotations, flips, contrast adjustments) to improve generalization.

Step 3: Model Design and Implementation

- Select an initial Convolutional Neural Network (CNN) architecture (e.g., UNet or EfficientNet) for image classification.
- Train the model using Caffe or TensorFlow frameworks with tuned hyperparameters (learning rate, batch size, epochs).
- Evaluate the model using cross-validation to prevent overfitting.

Step 4: Model Evaluation and Validation

- Assess model performance using accuracy, precision, recall, and F1-score metrics.
- Compare model predictions against ground truth or field-verified data where possible.
- Analyze misclassifications to identify limitations related to data quality or model bias.

Step 5: Visualization and Reporting

- Generate damage maps highlighting affected infrastructure within the pilot region.
- Use GIS platforms (e.g., QGIS or ArcGIS) to visualize spatial patterns of destruction.
- Prepare a comprehensive report summarizing technical results, limitations, and recommendations for scaling up to national coverage.

Step 6: Documentation and Future Work

- Document all steps to ensure reproducibility and transparency.
- Outline potential improvements, such as integrating SAR data, testing Siamese or transformer-based architectures, and expanding geographic coverage in future phases.

8. Expected Results and Contributions

By the end of this project, the following results and contributions are expected:

1. A functional deep learning model (prototype) capable of detecting and classifying infrastructure damage from post-war satellite and aerial images.
2. A curated dataset of pre- and post-conflict imagery from selected Sudanese regions, properly labeled and preprocessed for research and future use.
3. Damage assessment maps visualizing the spatial distribution and severity of destruction within the pilot area.
4. A documented analytical report summarizing technical performance, challenges, and recommendations for improvement.
5. Academic contribution by providing a baseline framework for applying AI and remote sensing to post-conflict reconstruction in Sudan and similar developing regions.
6. Potential practical contribution to humanitarian organizations and policymakers by offering a rapid, data-driven approach to guide recovery priorities.

9. Project Scope

Included (In Scope)

- Development and testing of a deep learning model (CNN-based) for damage classification.
- Use of satellite and aerial imagery covering a limited pilot region within Sudan.
- Basic data preprocessing and labeling to prepare a usable training dataset.
- Evaluation of model performance and creation of damage visualization maps.
- Documentation of methods, challenges, and recommendations for future scaling.

Excluded (Out of Scope)

- Real-time, nationwide deployment of the model (to be considered in future phases).
- Detailed field-based validation due to security and accessibility constraints.
- Economic loss estimation or social impact analysis beyond physical damage.
- Development of a full operational web platform — only the analytical prototype will be implemented in this phase.

10. Project Plan & Schedule

Project Duration:

Start: 9 Nov 2025 **End:** 9 Feb 2026 (≈ 12 weeks)

Phase 1 – Foundations & Preparation (Weeks 1–3)

9 Nov – 30 Nov 2025

Goals:

- Study theoretical basics of Artificial Intelligence (AI) and Machine Learning (ML).
- Learn how Convolutional Neural Networks (CNNs) and Transfer Learning work.
- Get familiar with tools: Python, Jupyter, TensorFlow/PyTorch, and CVAT for labeling.
- Download and explore xView2 dataset for experiments.

Deliverables:

- Short AI learning notes.
- Environment setup (software + GPU).
- Sample code successfully runs on a few xView2 images.

Phase 2 – Data Collection & Labeling (Weeks 4–6)

1 Dec – 21 Dec 2025

Goals:

- Select a pilot Sudanese region (one small area).
- Collect pre/post-war images (from Maxar, Planet, or open sources).
- Crop patches (≈160×160 px) and label 500–1,000 images (damaged / undamaged).
- Prepare dataset splits (train / validation / test).

Deliverables:

- A clean, balanced Sudan dataset folder.

- Document explaining labeling process.
- Ready-to-train image set.

Phase 3 – Model Training & Fine-tuning (Weeks 7–9)

22 Dec 2025 – 11 Jan 2026

Goals:

- Pretrain model on xView2 (if not already pretrained).
- Fine-tune CNN (e.g., UNet or EfficientNet) using Sudan dataset.
- Apply data augmentation and validation.
- Compare metrics (accuracy, precision, recall, F1).

Deliverables:

- Trained model weights.
- Training/validation curves and logs.
- Brief summary of experimental results.

Phase 4 – Evaluation, Mapping & Reporting (Weeks 10–12)

12 Jan – 9 Feb 2026

Goals:

- Evaluate model on test region (Sudan).
- Generate **damage maps** (visual results).
- Analyze errors and limitations.
- Write **final report** (chapters, discussion, conclusion).
- Prepare for presentation or defense.

Deliverables:

- Final report draft.

- Maps and accuracy charts.
- Documented methodology and results.
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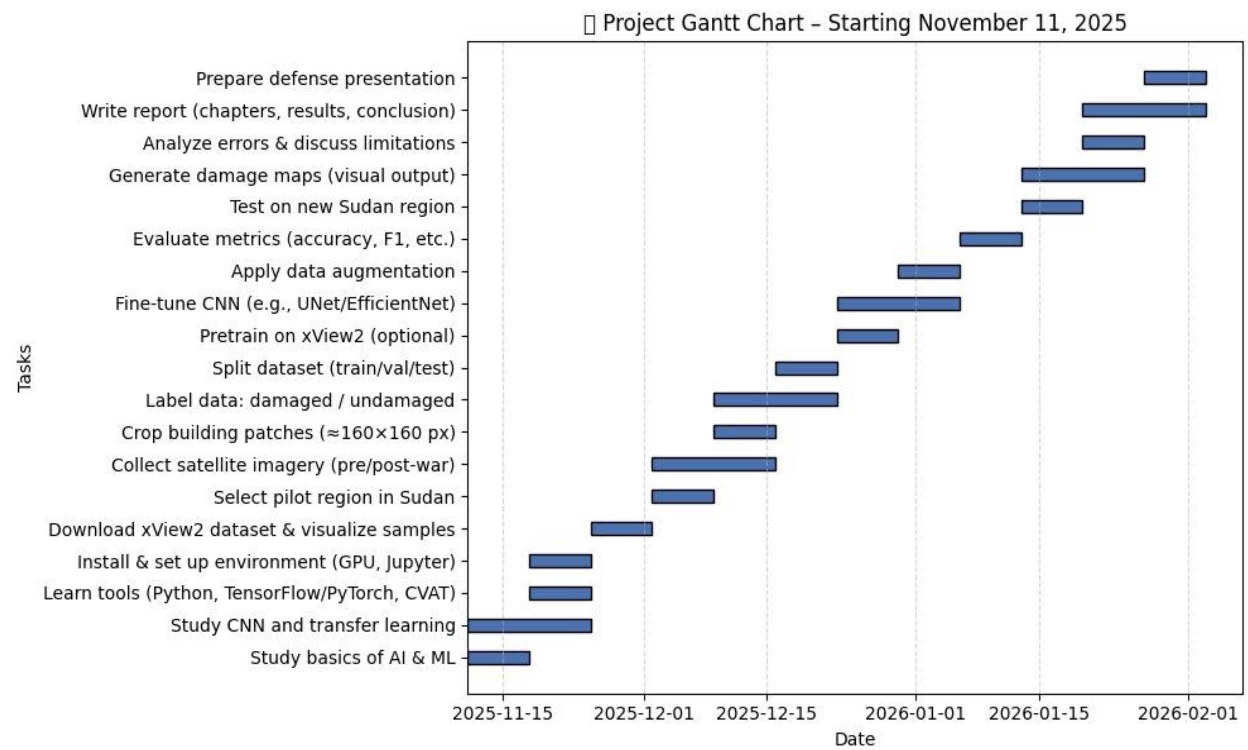
Schedule



(Gantt Chart shows the project schedule)

11. Proposed Thesis / Report Structure

Chapter	Title	Main Content
Chapter 1	Introduction	Background, problem statement, objectives, research questions, scope.
Chapter 2	Theoretical Background	Concepts of AI, ML, CNNs, remote sensing, and damage assessment literature.
Chapter 3	Related Work	Review of previous studies (Fujita 2017, May 2022, Azimi 2024, etc.).
Chapter 4	Methodology and Framework	Data sources, dataset preparation, model design, training pipeline.
Chapter 5	Experiments and Results	Model setup, evaluation metrics, results, visual outputs.
Chapter 6	Discussion and Conclusion	Analysis of findings, limitations, recommendations, future work.
References		All cited studies in Harvard style.
Appendices		Supplementary figures, code snippets, sample labels, and evaluation tables.

12. References

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