# House boundary detection Via Satelite imagery

**Abstract:**
With the advent of deep learning-based techniques, automatic building extraction from satellite and remote sensing imagery has been developing quickly. Modern models have been presented in recent studies to handle the difficult process of building extraction, taking into account variables such as variations in sizes, forms, orientations, and textures. The UNet and ResNet50 models have been combined for semantic segmentation and creating mask refinement. Another method incorporates prior knowledge of the positions of the buildings with segmentation findings in order to provide precise building extractions. It combines a multiscale-aware deep neural network with a segmentation-prior conditional random field (CRF) approach. Additionally, a joint attention mechanism has been proposed to enable networks to concentrate on pertinent features while squelching noise and irrelevant information.

**Introduction:**
The detection of house boundaries in satellite imagery has become an essential task in urban planning, disaster management, and population estimation. This survey presents a concise overview of the state-of-the-art techniques, models, and datasets used for house boundary detection using satellite imagery. House boundary detection using satellite imagery has been an active area of research for several decades. Despite the progress made in satellite imagery and advanced lenses, detecting house boundaries and other objects from satellite images remains a challenging task. The ability to detect houses or housing blocks is crucial as it can help estimate the population changes in an area, identify discrepancies in tax collections, and study infrastructure changes due to urbanization and city expansion. However, the complexity of house boundaries, coupled with the presence of multiple other objects like roads, fields, trees, and other structures in satellite images makes image segmentation extremely difficult. Researchers have proposed several promising approaches to tackle this problem but no approach guarantees a perfect solution. Recent advances in machine learning and deep learning methods have shown promising results in detecting buildings from satellite images. While LiDAR-based techniques offer height information that is crucial to identify buildings from other structures like fields, they are limited by cost and availability. Given the widespread availability and low cost of satellite imagery, detecting house boundaries from these images remains an important area of research with many challenges yet to be overcome.

**Related Work:**
Building extraction from satellite and aerial images has been a challenging task for several years. However, with the advancements in deep learning techniques and the availability of high-resolution satellite and aerial images, researchers have proposed various methods to automatically extract buildings from these images. In this regard, several papers have been published that propose novel approaches to building extraction. One such paper is "Automatic Building Extraction on Satellite Images Using UNet and ResNet50" by Waleed Alsabhan and Turky Alotai. They proposed a deep learning-based approach that uses UNet and ResNet50 models for building extraction from satellite images. The authors preprocessed the satellite

images by enhancing their contrast and converting them to grayscale. They then applied the UNet model for semantic segmentation of the images to generate a building mask that highlights regions containing buildings. The ResNet50 model was then applied to refine the segmentation and obtain final building extraction results. The authors achieved an overall accuracy of 95.8% for building extraction on a dataset of 1700 high-resolution satellite images covering different urban and rural areas in Saudi Arabia.

Another paper titled "Building Extraction from High Spatial Resolution Remote Sensing Images via Multiscale-Aware and Segmentation-Prior Conditional Random Fields" by Qiqi Zhu, Zhen Li, Yanan Zhang, and Qingfeng Guan presents a method for automatic building extraction from high-resolution remote sensing images using a multiscale-aware and segmentation-prior conditional random field (CRF) approach. This method involves training the model on images of different scales to capture building features at different levels. The authors first preprocess the remote sensing images by enhancing their contrast and reducing noise before extracting features using a multiscale-aware deep neural network. These features are then fed into a segmentation prior CRF model that combines segmentation results with prior knowledge of building locations obtained through a segmentation-based method.

In addition to these papers, "Building Extraction from Very High-Resolution Aerial Imagery Using Joint Attention Deep Neural Network" proposes a deep learning-based approach that uses a joint attention mechanism for building extraction from very high-resolution aerial imagery. The authors aim to solve the challenges of building extraction, such as the presence of small and large buildings, different orientations, and varying lighting conditions. Their proposed method achieved a state-of-the-art performance with an F1-score of 0.874 and 0.831 on two datasets.

Moreover, "Deep learning on edge: Extracting field boundaries from satellite images with a convolutional neural network" presents a novel approach for extracting field boundaries from satellite images using a Convolutional Neural Network (CNN). The authors used a U-Net-like architecture to predict field boundary masks from satellite images. To evaluate their method, they conducted experiments on two public datasets and compared their proposed method against several state-of-the-art methods such as Mask R-CNN, UNet++, and DeepLabv3+. The results demonstrate that their CNN-based framework outperforms existing methods in terms of various evaluation metrics like Intersection over Union (IoU), F1-score, Precision, Recall, and Mean Average Precision (mAP).
In conclusion, deep learning techniques have shown promising results in building extraction from satellite and aerial images. Researchers have proposed various approaches that utilize semantic or instance segmentation models to extract buildings or field boundaries accurately. Proper dataset selection and annotations are crucial for training these models effectively. Evaluation metrics such as IoU, F1-score, and mAP can be used to measure the performance of these models accurately.

**Datasets:**
In our research, we are using two datasets Aerial imagery dataset and the DHA Lahore dataset.

**Experiments:**

Our project aimed to develop an effective deep learning-based approach for house boundary detection using satellite imagery. We began by fine-tuning the Deeplabv3_resnet101 model on our custom DHA Lahore dataset. The dataset comprised two folders: masks and images. To utilize this dataset, we had to overcome several challenges, including converting the original dataset from geojson format to our desired shape and form, and setting up a one-hot conversion for the mask. This initial preparation was crucial for the success of our experiments.

1. **Baseline Model:** Our first experiment involved running the fine-tuned baseline model using binary cross-entropy loss. After addressing numerous challenges and ensuring the proper setup, we obtained an initial Intersection over Union (IoU) score of 0.614 for the test dataset. Although this result was a good starting point, we believed there was room for further improvement.
2. **Loss Function Exploration:** We then sought to identify better loss functions to improve the model's performance. We experimented with various loss functions, including Focal loss, Tversky loss, and combinations of different loss functions. After extensive experimentation, we discovered that our custom ensemble loss yielded the best results. This loss function combined binary cross-entropy (BCE) with Dice loss, allowing us to leverage the advantages of both methods.
3. **Custom Ensemble Loss:** Incorporating the custom ensemble loss into our model led to a significant improvement in the test IoU score, which increased to 0.706. This demonstrated the effectiveness of our custom ensemble loss in addressing the challenges of house boundary detection in satellite imagery.
4. **Optimizer and Scheduler Selection:** To further enhance our model, we tested various optimizers, including Adam, RMSprop, and SGD, along with different learning rates and weight decay values. Ultimately, we found that the Adam optimizer with a suitable learning rate and weight decay provided the best performance. Additionally, we introduced a scheduler to help the model find local minima more effectively. While this improved the IoU score, the increase was not as significant as the change in the loss function.
5. **Data Augmentation and Preprocessing:** To improve generalization and robustness, we experimented with several data augmentation techniques, such as rotation, flipping, and random cropping. Moreover, we explored various preprocessing techniques, including image normalization and contrast enhancement. These approaches contributed to the overall improvement of our model's performance.

**Results:**

After incorporating the above improvements and conducting extensive experimentation, we achieved the following results:

1. Baseline Model (Binary Cross-Entropy Loss): Test IoU score of 0.614.

2. Model with Custom Ensemble Loss (BCE + Dice Loss): Test IoU score of 0.706.
3. Model with Custom Ensemble Loss, Optimizer, Scheduler, and Data Augmentation: Test IoU score slightly higher than 0.796.

**Conclusion and Future Work:**

The most significant improvement in the IoU score was observed when we changed the loss function from binary cross-entropy to our custom ensemble loss. Although the scheduler and other enhancements did not lead to a substantial increase in the IoU score, they still contributed to the model's overall performance.

In conclusion, our comprehensive experiments demonstrated that a combination of Deeplabv3_resnet101, custom ensemble loss, optimizer, scheduler, and data augmentation can lead to a higher IoU score for house boundary detection via satellite imagery. This improved model may have potential applications in urban planning, disaster management, and population estimation. Future research can explore other techniques, such as attention mechanisms or multiscale-aware models, to further enhance the performance of house boundary detection from satellite imagery.

**Citations:**

Zhu, Q., Li, Z., Zhang, Y., & Guan, Q. (2020). Building extraction from high spatial resolution remote sensing images via multiscale-aware and segmentation-prior conditional random fields. *Remote Sensing*, *12*(23), 3983.

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