Comparison of Deep Learning Models with Different Backbones for Building Footprints Extraction in Dense Residential Areas of Bhaktapur

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KEYWORDS

Building Extraction, Transfer Learning, Dense Residential Area, Semantic Segmentation

ABSTRACT

The rapid advancements of Artificial Intelligence, particularly deep learning, has enhanced features extraction mainly building footprints. However, models trained on developed countries struggle to perform better while testing on the datasets of high-density residential areas of developing countries like Nepal. This research aims to improve the performance of the models by developing and utilizing a region-specific dataset for Bhaktapur. Initially, models like Unet, PSPNet and LinkNet with different backbone architectures like resnet18, resnet34, resnet50, and vgg19 were trained on the Massachusetts dataset and the performance was poor when tested with the dense residential areas of Bhaktapur datasets. To address this issue, new datasets of Bhaktapur were introduced for high density residential area where houses are closely attached. The datasets were prepared by digitizing each house on the high resolution orthomosaics which was then converted to mask. Subsequently, the orthomosaic was patches into 300 x 300 with the corresponding mask. These patches were split into training, validation and testing datasets. Models with different backbones were trained with custom datasets applying data augmentation techniques, including random clipping of 256 x 256, flipping and rotation to prevent overfitting and make the model more robust to variations in real world data. The models with different backbones were validated and tested, and the best performance was with LinkNet model with vgg19 backbone with an IoU of 94.29% and F1 Score of 98.29%, demonstrating good results for dense residential areas. This study highlights the importance or need of region based custom datasets to improve the accuracy of deep learning segmentation models for building extractions, mainly on unique urban structure which can be useful for urban spatial planning, and disaster risk management and monitoring.

1. INTRODUCTION

Building is the most important features that form the urban fabric. The distribution of buildings is changing due to urbanization and population growth, leading to an urban crawl on the peri-urbanization areas leading to high density residential areas. The changes in the spatial distribution of the building are very essential for the study of urban settlements, demographics, and so on (Li et al., 2019) . Traditional methods consume more time and effort to track the spatial distribution changes that necessitate the automated techniques for fast, accurate and error-free data.

The development of Machine Learning (ML) and Deep learning (DL) techniques, particularly Convolutional Neural Networks (CNN) and Artificial Neural Networks (ANN) are exponentially growing and also high accuracy for features extraction buildings have been demonstrated by different researchers using different deep learning approaches. Many researches on building footprints using deep learning for very high resolution (VHR) were carried out and a variety of new methods has been proposed which is beneficial for urban planning, disaster management, population estimation, and environment management (Feng et al., 2023). In the early stages, building footprints extraction were based on traditional image processing methods like edge, object and shadow-based methods (Ziaei et al., 2014). Chen et al. (2018) proposed an indices for edge regularity and shadow line which was employed in three machine learning classifiers: Adaboost, Support Vector Machine and Random Forest. Ok et al. (2013) proposed a fuzzy landscape modeling for directional spatial relationship between building and its corresponding shadows and GrabCut partitioning on VHR satellite images. These studies were based on the traditional methods to detect buildings. Nowadays, different deep learning approach have been used to segment building with higher segmentation accuracy.

Ronneberger et al. (2015) introduced U-Net architecture, designed for medical image segmentation, which was then widely used for building footprints extraction. Rastogi et al., (2022) introduced a novel CNN architecture, UNet-AP, which demonstrated superior performance than SegNet and UNet in terms of mean intersection over union. Similarly, residual U-Net model proposed by H. Wang & Miao (2022) for building footprint extraction claims to be a superior model than SegNet, FastFCN, Web-Net and DeepLabV3+. Some researchers have explored a variety of encoder-decoder architectures. For instance, Bakirman et al. (2022) compared different pretrained encoder with imagenet and concluded that the Unet++ architecture using SE-ResneXt101 encoder outperformed other models like Unet, DeepLabv3+, FPN and PSPNet. Similarly, Alsabhan & Alotaiby (2022) demonstrated the potentiality of automatic building footprint extraction using artificial intelligence in high-density residential areas using Unet model with resnet50 backbone.

Despite the advancements, numerous researches have been conducted on public datasets from developed countries such as Massachusetts, WHU, Inria, Waterloo. Kang et al. (2019) and Atik et al. (2022) performed experiments on Massachusetts, WHU aerial imagery, and Inria datasets for building segmentation. He et al. (2022) presented Waterloo building dataset with spatial resolution of 12cm which covers the area of Ontario, Canada for building footprints extraction. Atik et al., (2022) compared DeepLabV3 architecture with resnet-18, resnet-50, Xception, and mobilenetv2 backbones in Massachusetts, WHU and Inria datasets in which resnet-50 outperfoms other backbones in terms of F1 score and IoU score. B-FGC-Net has improved accurate extraction compared to Unet, Linknet and SegNet models in WHU and Inria building datasets (Y. Wang et al., 2022). Vincent M & P (2024) proposes a Mask-RCNN models which perform better than YOLO models in WHU and Inria datasets. They are limited to urban topography of developed countries which fail to capture the urban complexity and architectural diversity of dense urban of Nepal, particularly Nepal.

Our main contributions can be outlined as follows:

- Testing of dense residential areas on the model trained with Massachusetts datasets.

- Introduced new dataset of Bhaktapur which is a high-density residential area for building footprints extraction. This dataset captures house structure of developing nation, particularly Nepal, with attached buildings with tin, clay tiles and concrete roofs.
- Comparative study of different backbone architecture on performance of semantic models like Unet, Linknet and PSPnet with different backbones like resnet18, renset34, resnet50, and vgg19 during building extraction.

2. METHODOLOGY

2.1 Study Area

Bhaktapur Municipality is one of the oldest city of Nepal. It is smallest municipality of Nepal with an area of 6.88km^2 with population density of 12,070 per km^2 and lies at 1330 meters above the sea level. Geographically it extends from 27.66 ° North to 27.69 ° North and 85.399 ° East to 85.448 ° East. It is surrounded by 3 municipalities of Bhaktapur district, namely Changunarayan Municipality, Suryabinayak Municipality and Madhyapur Thimi Municipality.

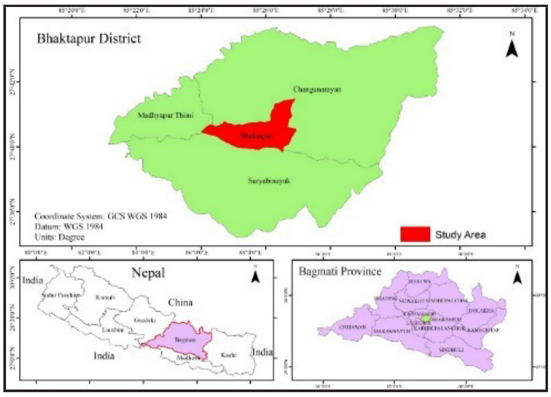

Figure 1: Study Area

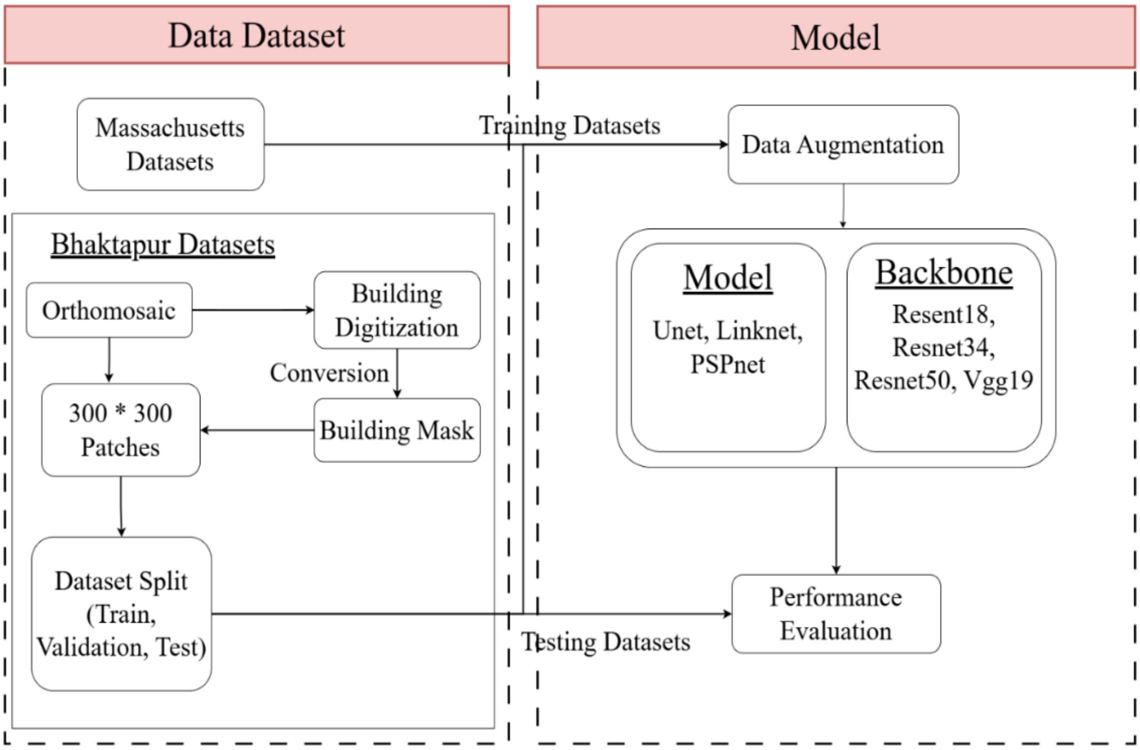

Figure 2: Methodology

2.2 Data Preparation

Massachusetts dataset of image 1500 x 1500 were split into 300 x 300 image size for both image and mask.

Digitization of the building's polygon were performed on the orthomosaic of Bhaktapur. The buildings features were converted to the mask images and split into 300 x 300 patches aligned corresponding to the RGB image which was uploaded in *Bhaktapur Building Dataset*[1] Subsequently, these datasets were split into training, validation, and testing datasets in 7:1.5:1.5 ratio for enough data to train a model and unbiased validation and testing of the model. [1]https://www.kaggle.com/datasets/romikgosai/bhaktapur-building-dataset

2.3 Model and Metrics

2.3.1 Models

2.3.1.1 Unet with Resnet Backbone

Figure 3 represents the deep learning architecture of Unet with Resnet backbone having encoder and decoder for semantic segmentation. The encoder utilizes a Resnet backbone with multiple layers. In encoder part, initially convolutional layer of 7 x 7 were applied to input image to extract low-level features and increase the number of channels. Then four layers of Resnet backbone were applied where residual blocks were applied in each layer to enhance feature learning and prevent vanishing gradients, followed by max pooling operations which decreases the spatial resolution. The extracted features are passed to decoder for up sampling to segment map. Decoder restore spatial resolution of the segmentation map by up sampling. Up-convolutional layers are applied to increase the feature map dimensions which are followed by concatenation that copy feature maps from encoder to retain spatial features. Finally, 1 x 1 convolutional layer refines feature representations to generate the final output segmentation map.

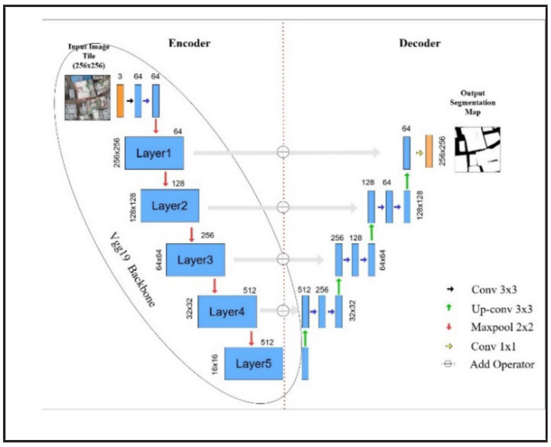

Figure 3: Architecture of Unet with Resnet backbone

2.3.1.2 Linknet with resnet Backbone

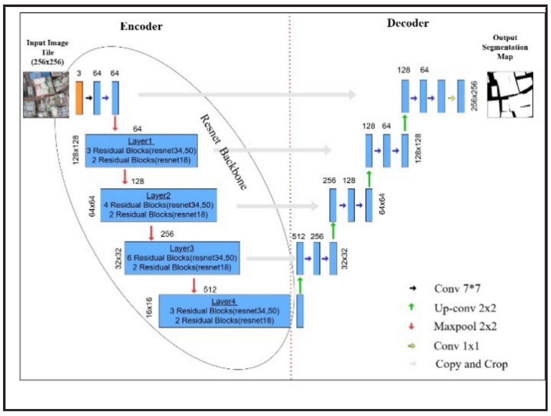

Figure 4: Architecture of Linknet with Vgg19

Figure 4 illustrates the deep learning architecture of Linknet with Vgg19 backbone, comprising of an encoder and decoder for building segmentations. In the encoder part, the encoder begins with 3 x 3 convolutional layer applied to the input image to extract low level features and increase the number of channels. It consists of the five layers utilizing Vgg19 backbone in which each layer consists of convolutional layer followed by 2×2 max pooling operations that decreases the spatial resolution and increases the feature depth. Decoder restore spatial resolution by up sampling the encoded features. Feature map dimensions are increased by applying up-convolutional layers and add operator facilitates feature fusion across different layers. Finally, final output segmentation is generated by refining the feature representations by applying 1 x 1 convolutional layer.

2.3.1.3 PSPNet with Backbone

Pyramid Scene Parsing Network (PSPNet) was introduced to extract global and local information about the overall scene. As in figure 5, backbones are utilized to extract features from the input image. Pyramid Pooling module process generated feature map by gathering multiscale information, integrating four parallel feature representations at different scales. Subsequently, the processed features are up sampled to original resolution and a final convolutional are applied which refines the output.

Three semantic segmentation models-Unet, PSPNet, and LinkNet were developed and trained with the custom dataset. Backbones were integrated with the models in which backbones serve as encoder and decoder components were composed of the respective model. Backbones has pre-trained networks which extract hierarchical features from input data that can learn the intricate patterns. Integration of backbones with the semantic models improve performance, avoid overfitting, and makes training faster.

In this study, for semantic segmentation of building footprints, the experiments were conducted with three models: Unet, PSPNet and Linknet with different backbones like resnet18, resnet34, resnet50, and vgg19. A default learning rate of 0.0001 was used for the stable and gradual updates to the model's weights. Further, an Adam optimizer, which iteratively updates the weights of networks leading to faster convergence and sigmoid activation function for binary classification were used. Different numbers of epochs were investigated to get the optimum value for training in the model training process i.e. the highest accuracy was obtained within 100 epochs for all models. That's why 100 epochs were used for training. The models were evaluated in each epoch using the validation dataset, early stopping was used when the accuracy tends to decrease which prevents overfitting. Different batch size of 16, 32, and 64 were used during the training. Batch size of 32 was chosen for having the highest performance. IoU and F1 Score are used as performance metrics. Binary cross entropy loss function was used for binary segmentations which help model to learn the probabilities of each class. Data augmentation techniques was applied to enhance generalization of model and to prevent overfitting by increasing the size and diversity of the training datasets adopting different geometric transformations like rotation, flipping, and rotation. The experiment was performed in Kaggle platform with its default GPU.

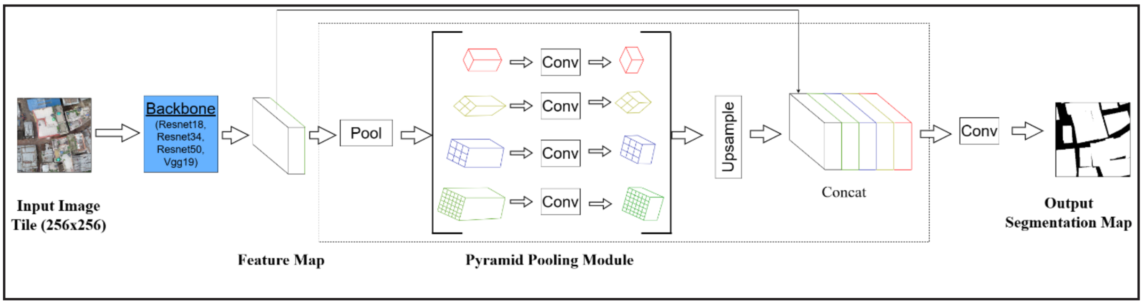

Figure 5: PSPNet Architecture

Table 1: Model Training Parameters

Parameter	Models		
	Unet	PSPNet	Linknet
Backbone	Resnet18, Resnet34, Resnet50, Vgg19		
Weight	ImageNet		
Learning Rate	Default (0.0001)		
Optimizer	Adam		
Metrics	F1-Score, IoU Score		
Loss Function	Binary Cross Entropy		
Number of Epochs	100		
Batch Size	32		
Activation Function	Sigmoid		
Data Augmentation	Horizontal Flip, Vertical Flip, Random Cropping, Random Rotation		
Callbacks	Early Stopping, Model Checkpoint		
Input shape	256*256*3 (RGB Images)		
Output	1 channel mask (Binary Segmentation)		

Initially, the models were trained and tested with the Massachusetts datasets and then again tested with the custom datasets of Bhaktapur. The performance of the models was evaluated for both Massachusetts and Bhaktapur datasets to assess their effectiveness across different geographical contexts. Subsequently, the models were trained with the Bhaktapur datasets and tested to assess performance of the models.

2.3.2 Evaluation Metrics

The performance of the models was evaluated using IoU, precision, recall, and F1 Score. IoU represents the overlap percentage between the ground truth and prediction output. Precision indicates the accuracy of positive predictions. Recall indicates sensitivity or ability to identify the true positive rates. F1 Score is the harmonic mean of the precision and recall.

Precision is the ratio of the number of correctly predicted positive samples to the number of all predicted positive samples (Norelyaqine et al., 2023).

$$\text{Precision} = \frac{TP}{TP+FP} \tag{1}$$

Recall is the ratio of the number of correctly predicted positive samples to the number of all positive samples in the test set.

$$\text{Recall} = \frac{TP}{TP+FN} \tag{2}$$

F1Score is the geometric mean between precision and recall.

$$F_1\ \text{Score} = \frac{2\times\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} \tag{3}$$

IoU is the ratio of intersection between the target and the prediction.

$$\text{IoU} = \frac{TP}{TP+FN+FP} \tag{2}$$

3. RESULTS

Qualitative and Quantitative evaluations of building footprints extraction results for Massachusetts and Bhaktapur datasets are provided in this section.

3.1 Qualitative Results

Few random images from the testing datasets are selected and segmented with different models and backbones which are then compared with ground truth. The sequence below image begins with original image followed by ground truth and then the segmentation results of Linknet, Unet and PSPNet models. Each model was tested in the series of Vgg19, Resnet18, Resnet34, and Resnet50.

Figure 6 represents the original image with its ground truth and the segmentation of building footprints generated by different models on the Massachusetts datasets. Linknet and Unet shows higher performance while PSPNet performs significantly worst. It may be due to loss of finer spatial details in PSPNet which relies on pyramid pooling module that captures global context(Yuan et al., 2022).

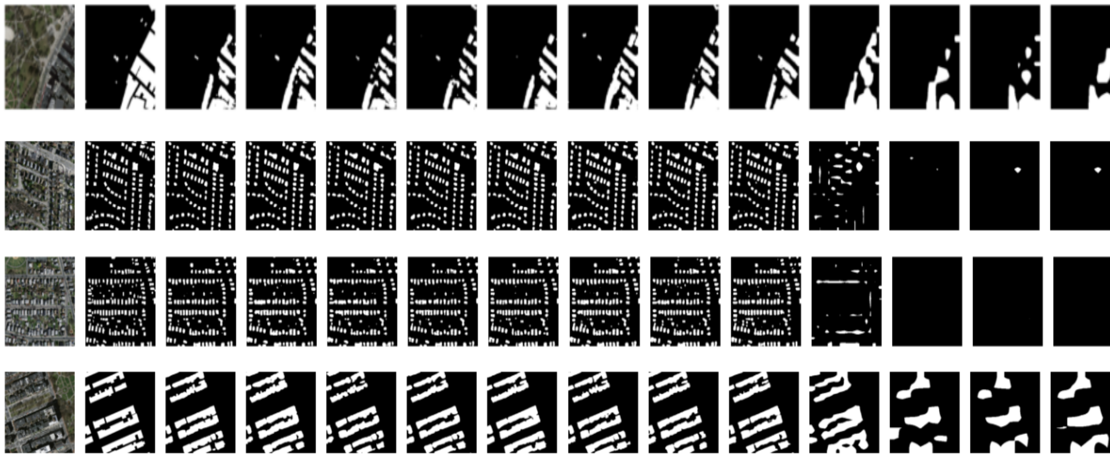

Figure 6: Performance comparison on the Massachusetts building dataset. (a) Original Image, (b) Ground Truth (c) Linknet-Vgg19, (d)Linknet-resnet18, (e)Linknet-resnet34, (f)Linknet-resnet50, (g) Unet-Vgg19, (h) Unet -resnet18, (i) Unet -resnet34, (j) Unet -resnet50, (k) PSPNet-Vgg19, (l) PSPNet -resnet18, (m) PSPNet -resnet34, and (n) PSPNet -resnet50

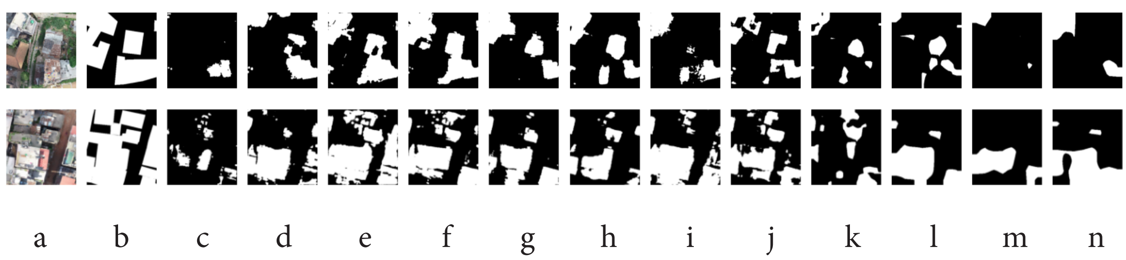

Figure 7: Performance comparison on the custom dataset with Model trained in Massachusetts. (a) Original Image, (b) Ground Truth (c) Linknet-Vgg19, (d)Linknet-resnet18, (e)Linknet-resnet34, (f)Linknet-resnet50, (g) Unet-Vgg19, (h) Unet -resnet18, (i) Unet -resnet34, (j) Unet -resnet50, (k) PSPNet-Vgg19, (l) PSPNet -resnet18, (m) PSPNet -resnet34, and (n) PSPNet -resnet50

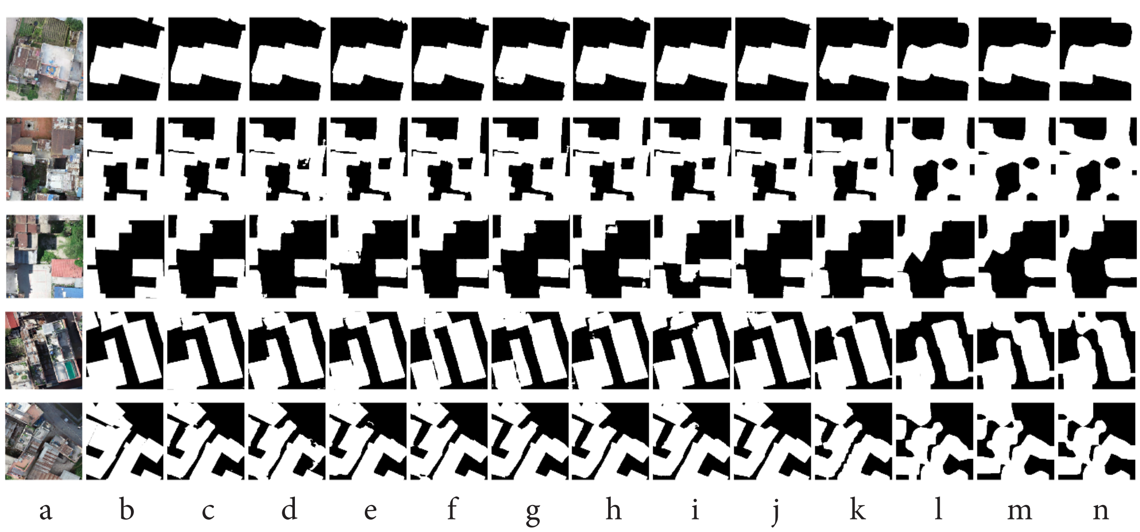

Figure 8: Performance comparison on the custom dataset (a) Original Image, (b) Ground Truth (c) Linknet-Vgg19, (d)Linknet-resnet18, (e)Linknet-resnet34, (f)Linknet-resnet50, (g) Unet-Vgg19, (h) Unet -resnet18, (i) Unet -resnet34, (j) Unet -resnet50, (k) PSPNet-Vgg19, (l) PSPNet -resnet18, (m) PSPNet -resnet34, and (n) PSPNet -resnet50

Figure 7 represents the original image with its ground truth and the segmentation of building footprints generated by various models trained on the Massachusetts datasets and tested on the Bhaktapur datasets. Almost all models perform worst results due to distinct building patterns of Bhaktapur compared to Boston areas used for training.

Figure 8 represents the original image with its ground truth and the segmentation of building footprints generated by various models on the Bhaktapur datasets. Model with Vgg19 shows better results compared to ResNet backbone due to higher number of parameters (Kamal & EZ-ZAHRAOUY, 2023).

3.2 Quantitative Results

This section represents the performance of models in various backbone architectures in terms of IoU and F1Score on Massachusetts and Bhaktapur datasets.

Table 2 represents the IoU and F1 Score for each model trained and tested with the Massachusetts dataset. Unet and Linknet perform significantly better compared to PSPNet across all backbones.

Table 2: Models Performance on Massachusetts Test Datasets

Model	Backbone	IoU	F1 Score
UNet	Resnet18	0.609	0.787
	Resnet34	0.585	0.770
	Resnet50	0.615	0.791
	Vgg19	0.606	0.787
LinkNet	Resnet18	0.590	0.774
	Resnet34	0.554	0.745
	Resnet50	0.577	0.765
	Vgg19	0.612	0.789
PSPNet	Resnet18	0.050	0.141
	Resnet34	0.061	0.166
	Resnet50	0.062	0.174
	Vgg19	0.261	0.498

Table 3 summarizes the performance of models with different backbones trained with Massachusetts datasets and tested with Bhaktapur datasets. The results on all models plummeted significantly in performance due to difference in building pattern of Bhaktapur compared to Boston areas.

Table 3: Models trained on Massachusetts Datasets Performance Evaluation on Bhaktapur Datasets

Model	Backbone	IoU	F1 Score
UNet	Resnet18	0.109	0.239
	Resnet34	0.165	0.354
	Resnet50	0.199	0.389
	Vgg19	0.152	0.321
LinkNet	Resnet18	0.196	0.389
	Resnet34	0.395	0.659
	Resnet50	0.244	0.450
	Vgg19	0.035	0.081
PSPNet	Resnet18	0.119	0.280
	Resnet34	0.099	0.201
	Resnet50	0.097	0.237
	Vgg19	0.055	0.126

Table 4 presents the results of models on Bhaktapur datasets. The performance of all models and backbones on Bhaktapur datasets are significantly high compared to Massachusetts datasets. Unet and LinkNet has better performance compared to PSPNet. Linknet with Vgg19 backbone has best performance among all model-backbone. Overall, models using VGG19 backbone outperform every ResNet backbone.

Table 4: Models performance on Bhaktapur Test datasets

Model	Backbone	IoU	F1 Score
UNet	Resnet18	0.929	0.978
	Resnet34	0.929	0.979
	Resnet50	0.934	0.981
	Vgg19	0.939	0.982
LinkNet	Resnet18	0.916	0.975
	Resnet34	0.926	0.978
	Resnet50	0.935	0.981
	Vgg19	0.943	0.983
PSPNet	Resnet18	0.856	0.947
	Resnet34	0.866	0.952
	Resnet50	0.868	0.954
	Vgg19	0.924	0.975

4. DISCUSSION AND CONCLUSION

4.1 Discussion

The results from this research indicate that the deep learning models for building footprints extraction trained on developed countries does not generalize well for the high-density residential areas of developing countries, particularly Bhaktapur of Nepal. Models' performance improved with the introduction of the Bhaktapur datasets. Linknet with Vgg19 backbone performed best with the introduced datasets with an IoU Score of 94.29% and F1Score of 98.29%. Linknet and Unet perform better in comparison to PSPNet due to use of skip connections emphasizing on local feature map, while UNet shows strong consistency across datasets. Models with higher number of layers in Resnet backbone has better segmentation results due to higher number of parameters.

Research by (Alsabhan & Alotaiby, 2022) demonstrated the best performance was in Unet model with Resnet50 backbone for high density residential areas using but with our introduced datasets this model ranked second highest after Linknet with Vgg19. Vgg19 backbone for all models performed well in our research which indicates that Vgg architectures are well suited for semantic segmentation that matches with previous studies like of (Norelyaqine et al., 2023), where the best results were achieved on Unet with Vgg16.

4.2 Conclusion

This study evaluated the performance of three semantic segmentation models with different backbone networks (ResNet18, ResNet34, ResNet50, and VGG19) for building footprints extraction on two location's datasets Massachusetts and Bhaktapur. The models trained solely on Massachusetts datasets performed poor while tested on the Bhaktapur datasets which highlights the limited generalizability of models trained on developed countries data to developing countries data. All models performed significantly better results when trained and tested on Bhaktapur datasets, with LinkNet model having Vgg19 encoder had the highest accuracy in terms of IoU and F1 Score. This performance highlights the cruciality of adapting training data to the local context for accurate segmentation. The findings of this research indicate crucial role of adapting training data to the local context for accurate segmentation.

Overall, the results highlight the need of context-specific data in training segmentation models for building footprints extraction task. This research features good performance of VGG architectures when paired with UNet and LinkNet models.

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ACKNOWLEDGEMENT

We are grateful to Bhaktapur Municipality and Khwopa College of Engineering for providing the orthomosaics of Bhaktapur Municipality

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