Recognition of floor plans has been a challenging and popular task. However, existing approaches are struggling to make accurate room-level unified predictions, seriously limiting their visual quality and applicability. In this paper, we propose a novel approach to recognize the floor plan layouts with a newly proposed Offset-Guided Attention mechanism to improve the semantic consistency within a room. In addition, we present a Feature Fusion Attention module that leverages the channel-wise attention to encourage the consistency of the room, wall, and door predictions, further enhancing the room-level semantic consistency. Experimental results manifest our approach is able to improve room-level semantic consistency and outperforms the existing works both qualitatively and quantitatively. To summarize, this paper tackles inconsistent semantic prediction issues in floor plan segmentation and enhances visual plausibility, quantitative performance, and practical applicability.

INDEX TERMS
Floor plan recognition, attention, offset-guided, convolutional neural network.

I. INTRODUCTION
The recognition of floor plan elements has been a useful task that provides benefits to various applications such as indoor robotics navigation, computer-aided home design, and VR/AR. However, it is a challenging task beyond the general semantic segmentation problem. First, different from the common objects in natural images, rooms in the floor plan images typically share the similar rectangular shape as shown in Fig. 1, so it is challenging to identify their semantic categories simply based on their appearances. Second, the relative spatial locations of rooms are crucial to floor plan image understanding. However, traditional CNNs for semantic segmentation typically possess the translational invariance property, incapable of effectively capturing the rooms' relative spatial information in floor plan images. Third, the floor plan images typically lack textures, which plays a key role in CNNs' recognition as suggested by existing works like [36]. Therefore, directly adopting the semantic segmentation networks designed for natural images to this task cannot produce satisfactory results due to the above issues, and quantitative proofs are provided in our experiments.

Recently, many approaches have been proposed to address the floor plan recognition task through convolutional neural networks and provided promising results. However, their models typically lack the capability of room-level understanding. To be more specific, they predict the semantic label of each pixel individually and may assign multiple semantic categories in one single room as shown in Fig. 1 (b, c), which severely limits their applicability in practical applications. The above issue is potentially induced by the following causes. First, the rooms vary from each other significantly in terms of size; yet, their approaches cannot effectively capture both the global and local information to handle the large and tiny sized rooms respectively. Second, they typically predict the room and boundary categories (wall, door) parallelly, thus the predictions on these categories may be inconsistent with each other. A simple approach to address this issue is to leverage flood fill, i.e., assign all the pixels in a room to be the same category according to majority voting. However, this approach still cannot work well due to the reasons that will be discussed in Section II.
In this paper, we propose a novel approach to address the above issues in existing approaches to improve the prediction consistency within a single room and the overall floor plan segmentation performance. First, we design an Offset-Guided Attention network to encourage consistency within each room. To do this, we utilize a simple prior that “all the pixels of the same room share the same semantic category”, which always holds true in all the existing datasets as far as we know, but is ignored by the current state of the arts. Our network explicitly learns the correlation of pixels within each room with our newly proposed offset prediction module, and the learned correlation is further utilized to refine the output and improve the consistency of predictions within each room. In addition, our Offset-Guided Attention module helps the network to learn long-range context information and increase the effective receptive field of the network; hence, our approach can handle large and long rooms and have consistent semantic predictions in them (see Fig 1 (d)).

Besides, we propose a Feature Fusion Attention module to further improve the consistency between room and boundary predictions. Existing works [1] propose to predict the room and boundary categories in individual branches to improve the results, which have been proven to be effective. However, this strategy has a side-effect that the prediction of the two branches may be inconsistent with each other. As shown in Fig 1 (b), the blue room is dilated into the orange room while the wall prediction does not recognize any boundaries between blue and orange, which shows that the prediction of the boundary categories is not aligned with the room. Similarly, there are also cases where a boundary is successfully recognized by the boundary branch, but not recognized by the room branch. This is another cause of the semantic inconsistency within a single room. To address this issue, we present a Feature Fusion Attention module to combine the prediction of two branches and yield consistent predictions (Fig 1 (d)).

Quantitative experiments manifest that our approach outperforms the existing works on two commonly used floor plan recognition datasets [4], [10] consistently. In addition, qualitative comparisons show that our Offset-Guided Attention and Feature Fusion Attention effectively improve the room-level consistency. Code and models will be released upon publication.

To summarize, this paper has the following contributions:

1) We propose an effective and interpretable framework for floor plan segmentation beyond the existing works;
2) We propose an Offset-Guided Attention module and a channel-wise Feature Fusion Attention module to improve the room-level semantic prediction;
3) We achieve state-of-the-art performance on the two common floor plan recognition datasets R2V [4] and R3D [10].

II. RELATED WORK
A. SEMANTIC SEGMENTATION
Semantic segmentation aims to recognize the pixel-wise semantic categories in the image. After Long et al. [12] propose to utilize the Fully Convolutional Networks to address this issue, remarkable signs of progress are made in this field [13], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [30], [31], [32]. For example, [13] proposes a convolutional network that includes both downsampling and upsampling paths to improve the prediction performance, and [15] presents an Astrous Convolution operation to expand the receptive field of the network. Afterwards, [17] proposes HR-Net to maintain the high-resolution representations throughout the network. As discussed in Section I, floor plan segmentation is drastically different from the general semantic segmentation. In this work, we propose some particularly designed novel modules for floor plan segmentation and manifest their effectiveness in this challenging task.

B. TRADITIONAL APPROACHES ON FLOOR PLAN RECOGNITION
Floor plan recognition aims to derive the pixel-level prediction of a floor plan image. However, it is notably different from semantic segmentation, as discussed in Section I. This task attracts a lot of attention from both academia and industry in the past few years [1], [2], [2], [5], [6], [7], [11], [26], [27], [28], [29]. For example, [1] proposes attention and contextual module to increase the awareness of the boundary information, and [2], [5] further improve the floor plan recognition accuracy. Besides, [7], [26], [27] work on the reconstruction of 3D models from floor plan layouts. Traditional methods [5], [6] use low-level information like graphical shapes to predict rooms and boundaries. Ahamed et al. [2] propose to decouple boundary recognition and text recognition from room recognition, and they introduce extracting line segments of different thicknesses – the thicker ones are considered to be the walls and the thinner ones are the texts. In addition, another approach [7] utilizes a heuristics method for this task. However, the performance of this heuristics-based approach is far from satisfactory as the assumptions of this approach cannot cover all the circumstances. Besides, models using this heuristics-based approach need to be fine-tuned manually in a very frequent manner and many parameters need to be tuned for specific datasets.
FIGURE 2. Overview of our framework. We extract features using a CNN backbone(1); then use the feature to generate an offset prediction(2), which will later be used to determine the affinity in the Offset-Guided room attention module(3); besides, an additional feature extraction branch is used to enrich the room and boundary features by fusing them with the Feature Fusion Attention module(FFA)(4), and then produce the final boundary and room prediction(5). Note that the English labels on the "input image" are added for the reader's reference and do not exist in the original image.

C. ROOM-LEVEL CONSISTENCY IN FLOOR PLAN RECOGNITION

Recently, a variety of approaches [1], [2], [11] is proposed to address the floor plan recognition task using convolutional neural networks, which yielded promising results. However, as discussed in Section I, they typically predict inconsistent semantic categories within one single room (see Fig 1 (a,c,d)), which implies that their models lack room-level understanding.

An intuitive idea to address this issue is to leverage a post-processing method flood fill, which simply assigns all pixels within a certain boundary to the same semantic label according to the majority voting. An intuitive idea to address this issue is to leverage a post-processing method, flood fill, which assigns all pixels within a specific boundary to the same semantic label according to the majority voting. However, it cannot achieve satisfactory performance. That is because the boundary (door and wall categories) segmentation that flood fill is based upon a challenging task. Specifically, in many cases, the boundaries are predicted in an inaccurate or even wrong location. In addition, flood fill requires the boundary to be continuous and form a closed space to conduct the majority voting – any slight failure in boundary prediction could cause a huge room-level prediction error, as shown in Fig 1 (d).

Some existing works try to enhance the accuracy of boundary prediction. However, flood fill still cannot work well based on their approaches due to their unsatisfactory boundary prediction performance. However, due to unsatisfactory boundary prediction performance, flood fill still cannot work well on top of their approaches. Liu et al. [4] design a network that recognizes the junction point of the floor plan and determines the position of boundaries based on such prediction. However, the method can only recognize horizontal and vertical boundaries and cannot work well for others, which significantly limits its applicability. Besides, Zeng et al. [1] design a network with boundary-aware kernels and successfully bring up the accuracy of boundary predictions. Nevertheless, their boundary accuracy is still not high enough for flood fill, and the network has an inferior accuracy in certain types of rooms, where in many cases the majority of pixels predicted in a room are of the wrong category. In a word, even though existing works [1], [4] address on the boundary accuracy, the simple approach like flood filling still fails to improve the room prediction consistency and the overall accuracy.

D. ATTENTION MECHANISM IN FLOOR PLAN RECOGNITION

Early works like [8] propose using self-attention mechanism to increase awareness of the correlation between different
words in a sentence. Recently, some existing works adopt the attention mechanism in floor plan recognition. Zeng et al. [1] are the first to use attention in this task. They design a direction-aware kernel supported by room-boundary guided attention to encourage recognition of the spatial relationship between boundaries and rooms. With such a method, the accuracy of wall prediction is largely increased, but room prediction remains to be an issue. Recently, Lv et al. [3] further enhance the accuracy of the room and boundary prediction with the architecture to jointly detect and learn text, symbol, structural element, and scale information. However, since their approach relies on the text and symbol prediction, [3] only works on their own dataset but cannot be applied to the general floor plan datasets like R3D and R2V, since the symbols in these datasets have different styles and the texts are even in different languages. Besides, text and symbol recognition usually cause a significant increase in the network complexity.

III. METHOD

A. OVERVIEW

Figure 2 illustrates the architecture of our network. We utilize a backbone network with an 8x downsampling rate to extract features from the input image. After the backbone network, we employ a deconvolution followed by a convolution to upsample the feature map by 2 times and reduce the number of channels from 2048 to 64. This upsampling process results in a feature map size that is 1/4 of the original image size. After resizing, the prediction head of the network contains four branches: boundary prediction, room prediction, Offset-Guided Attention, and Feature-Fusion Attention. Boundary prediction (Fig 2 (4)) is to predict boundary categories, i.e., walls and doors. Room prediction (Fig 2 (5)) is to predict the semantic category of the pixels within rooms. Offset-Guided Attention refers to the prediction of the vertical and horizontal offset between the specific pixel \( p \) and the geometrical center \( c \) of the room \( R \) it belongs to. Feature-Fusion Attention aims to improve the consistency between the room and boundary predictions. Notably, inspired by [1], after feature extraction of the backbone network, we use two individual branches on the top of the backbone for room and boundary prediction respectively, as shown in Fig 2 (4, 5) to improve their performances. In the following, we will detail the key modules including the Offset-Guided Attention in Section III-B and Feature-Fusion Attention in Section III-C.

B. OFFSET-GUIDED ATTENTION MODULE

In the floor plan image, the semantic correlation between two pixels cannot be directly represented by their distance on the floor plan. As shown in Fig 3, pixels that are close to each other (p2, p3) can be hardly related in terms of semantic category since they belong to different rooms, whereas those that are far away (p1, p2) are semantically correlated with each other since they belong to the same room. Therefore, simply measuring the semantic correlation among pixels based on their Euclidean distance is an inferior approach, since this distance may not truly reveal the semantic correlation of the pixels. To resolve this issue, we observe that if the pixel is shifted towards the center of the room it belongs to, the distance of the shifted pixels can better reveal their semantic correlation (see p1, p2, and p3 in Figure 3). Based on the above semantic-aware distance measurement with the offset towards the room center, we propose an Offset-Guided Attention module to better measure the pixel correlation. Fig 4 shows the architecture of Offset-Guided Room Attention Module. First, as shown in Figure 4 (a), the offset prediction module predicts the offset \( o_p \) from each pixel \( p = (x, y) \) to the center of the room \( c_p \) it belongs to, i.e., \( o_p = c_p - p \). With equation

\[
p' = p + o_p
\]  

(1)

denoting the offset-guided shifted position of \( p \), we can measure the correlation \( A_{i,j} \) of two pixels \( p_i, p_j \) according to the Equation 2.

\[
A_{i,j} = \|p'_i - p'_j\|^2
\]  

(2)

If the pixels \( p_i, p_j \) are close to each other after the offset-guided shifting, then they are strongly correlated with each other, and hence have a better chance to be in the same room and also share the same semantic category. Then, the correlation \( A \) serves as the attention map of our Offset-Guided Attention module. In Fig 4 (c), we illustrate the mutual attention map of the pixels in one row \( l_i \) of the image \( I \). This sub attention map has the shape \( w \times w \) where \( w \) indicates the width of the image. It is the symmetric matrix where the diagonal values indicate the correlation to the pixel itself. In addition,
the attention of nearby pixels (in the same room) is significantly larger than others that are located in different rooms, and the sharp change of attention values in Fig 4 (c) manifest the effectiveness of our attention map \( A \) to distinguish the pixels within the same room or are in different rooms.

Then, the attention map \( A \) is normalized by softmax to make sure that \( \sum_j A_{i,j} \), i.e., the sum of attention values of all other pixels \( j \) to the target pixel \( i \), to be 1. Then the features from the room prediction branch \( f_j \) are weighted summed according to \( A \), and produce the enhanced feature \( \hat{f}_i \) for the target pixel \( i \), as shown in Equation 3.

\[
\hat{f}_i = \sum_j A_{i,j} f_j
\]  

At last, the enhanced feature \( \hat{f}_i \) is concatenated with \( f_i \) for the final semantic prediction. Note that here we take the pixel \( i \) as an example, and in our approach, all the pixels are operated in the same way.

To improve the memory and calculation efficiency, we adopt crisscross attention technique [9], where only the correlation between the target pixel \( i \) and other pixels \( j \) on its horizontal and vertical axis contribute to the attention map. Following [9], this module is applied two times successively in order to simulate the full attention. Please refer to [9] for more details.

C. FEATURE FUSION ATTENTION MODULE

As discussed in Section I, the predictions of room and boundary might be inconsistent with each other since the two branches introduced in Section III-A predict these two kinds of categories individually, as shown in Fig 1. To address this issue, we propose a Feature Fusion Attention module to fuse the features of the two branches with an additional shared branch, and enhance the prediction consistency of room and boundary branches. Fig 5 shows the architecture of Feature Fusion Attention module. First, the feature map from the two branches \( f_1, f_2 \in \mathbb{R}^{d \times h \times w} \) are concatenated in the channel dimension as \( f = f_1 \oplus f_2 \in \mathbb{R}^{2d \times h \times w} \), and a global average pooling layer reduces the size of \( f \) to be \( \in \mathbb{R}^{2d \times 1 \times 1} \). Then one fully connected layer learns a channel-wise attention map \( A \), of size \( 2d \times 2d \), indicating how each channel correlates to others, and outputs a weight feature \( w \in \mathbb{R}^{2d \times 1 \times 1} \), one element for each channel. At last, the enhanced feature map is derived with Equation 4.

\[
\hat{f} = f \otimes w
\]  

where the \( \otimes \) denotes the element-wise multiplication.

To summarize, the Feature Fusion Attention module leverages the shared features of the boundary and room prediction branches and feed the mutual information between them to improve their prediction consistency. Our Feature Fusion Attention Module is based on channel-wise attention, which is also adopted in Squeeze-and-Excitation (SE) blocks [37]. However, our Feature Fusion Attention has significant differences from the SE-Block. First, the two approaches are proposed to solve different problems. Our module is used to resolve the inconsistency between Room and Boundary branches and to harmonize the predictions for the two branches, whereas the SE block is a building block of the backbone to re-weight the channels of the feature map. Second, they have different structures. Our module involves three different branches. It assists the feature ensemble of the two previous prediction branches with an additional shared feature branch, whereas the SE block relates to only one branch and works in the backbone network.

D. LOSS FUNCTION

For both the boundary and room prediction, we use weighted softmax cross entropy loss with specific weight for different categories, as shown in Equation 5.

\[
\mathcal{L}_s = \sum_{i=1}^{C} -w_i \mathbb{1}(y_i) \log(p_i)
\]  

where \( C \) is the number of categories, \( w_i \) is the weight applied to the specific category, \( \mathbb{1}(y_i) \) is an indicator function and equals to 1 when the ground truth category of \( y \) is the category \( i \), \( p_i \) is the predicted possibility for the category normalized by the Softmax function. \( w_i \) is derived by calculating the percent
of pixels of the specific category in the training set:

\[ w_i = \frac{V_i}{V_{total}} \]  

(6)

where \( V_i \) is number of pixels of the specific category, and \( V_{total} \) is the total number of pixels.

For the offset prediction, we use \( L_1 \) loss to measure the distance of two pixels after offset-guided shifting, as shown in Equation 7.

\[ \mathcal{L}_o = |g_x - o_x| + |g_y - o_y| \]  

(7)

where \( g_x \) and \( g_y \) are the offset ground truth in x and y axis, and \( o_x \) and \( o_y \) are the predicted offset in x and y axis.

The overall loss to train the network is \( \mathcal{L}_s + \mathcal{L}_o \).

IV. EXPERIMENTS

A. DATASETS

We evaluate our Offset-Guided Attention Networks on two datasets that were commonly used for floor plan recognition, the R3D and R2V dataset [4], [10]. The R3D dataset consists of 214 images from [10], and the R2V dataset consists of 815 images from [4]. To have a fair comparison with existing works, we follow the same train-test split as [1].

B. IMPLEMENTATION DETAILS

Our network is trained on a single NVIDIA Tesla P100-PCIE GPU and is trained for 7k iterations in total. We adopted a fixed initial learning rate of 0.01 and used a weight decay of rate 0.0002. Besides, we use SGD with Nesterov Momentum and update parameters. The training is conducted in two steps. First, we initialize our network using the ResNet/VGG model pretrained on ImageNet and optimize the offset prediction module with other weights frozen. Then, we optimize other modules in our network with offset prediction branch frozen. In inference, we derive the final result by a single forward pass, without any post-processing like existing works [1], [3].

C. METRICS

Following the existing works [1], [4], we adopt overall accuracy and class accuracy as the metrics to evaluate the performance quantitatively as shown in Equation 8 and 9.

\[ \text{overall}_{\text{acc}} = \sum_{j=0}^{i} \frac{C(j)}{N(j)} \]  

(8)

\[ \text{class}_{\text{acc}}(j) = \frac{C(j)}{N(j)} \]  

(9)

where overall_{\text{acc}} denotes overall accuracy, class_{\text{acc}} denotes class accuracy of a specific class \( j \), \( i \) is the number of categories, \( C \) is the correctly predicted number of pixels of specific category \( j \), and \( N \) is the total number of pixels of specific category \( j \).

In addition, we also adopt \( m_{\text{IoU}} \) (mean Intersection over Union) as an additional metric, defined as the following equation:

\[ m_{\text{IoU}} = \frac{\sum_{j=0}^{n} C_j}{n} \]  

(10)

where \( n \) denotes the total number of categories, \( C_j \) is the correctly predicted number of pixels in a certain category, \( P_j \) is the total number of pixels predicted in a certain category, and \( G_j \) is the total number of pixels in the ground truth of certain category.

D. COMPARISON WITH THE EXISTING WORKS

We compare our network with existing floor plan recognition approaches Raster-to-Vector [4] and Deep Floor Plan [1], as well as general semantic segmentation approaches PSPNet [16] and DeepLabV3+ [15].

Fig 6 (c, e) shows visual comparisons of our result and Raster-to-Vector. Compared with the ground truth (b), Raster-to-Vector (e) fails to determine the room type of a major room in the top row. In addition, their model fails to recognize some room regions and leaves them empty. In contrast, our model shows perfect room type prediction and accurate recognition of boundary categories. As shown in Table 1 “Raster-to-Vector”, our result has superior performances in all categories and has significantly higher overall accuracy.

Next, we compare our result with general segmentation networks including DeepLabV3+ [15] and PSPNet [16]. We utilize the author-released code to produce their results. First, as shown in Fig 6 (c, f, g), in the top and bottom case, both DeepLabV3+ and PSPNet are not able to predict one or more rooms to be the unified category. Besides, there are inconsistencies between their boundary and room predictions, such as some nearby room categories are dilated into each other. In contrast, our network produces uniform and consistent results within rooms. Also, Fig 7 shows our network’s ability to produce superior results in the R3D dataset over the existing works. Table 1 “DeepLabV3+” and “PSPNet” show the quantitative comparison between our results and results of the two existing works on the R2V and R3D datasets. As shown in the table, our network produces significantly superior results in overall accuracy and all sub-classes in comparison with the other two networks in both R2V and R3D datasets. This result explicitly shows the superiority of our network over the general semantic segmentation networks, and also demonstrates the significant difference between the floor plan recognition task and the general semantic segmentation task.

We further compare our work with a recent floor plan recognition approach Deep Floor Plan [1]. Still, we utilize the author-released model and adopt the same experimental setting as in their paper. As shown in Fig 6 (d), in the middle case, there is a blue part predicted inside the orange room, indicating that their approach is incapable to have a consistent room-type prediction, and can make the wrong prediction when the room has the irregular shape. In addition, some predictions are dilated to the nearby rooms as shown in the bottom row, leading to inconsistent predictions with a single
FIGURE 6. Visual comparison of our result (c) with existing works (d-g), including Deep Floor Plan [1], R2V (Raster-to-Vector) [4], DeepLabV3+ [15], and PSPNet [16], on the R2V dataset. Note that the English labels in (a) do not exist in the original image, and are added for the reader’s reference.

TABLE 1. Quantitative comparison with Raster-to-Vector [4], DeepLabV3+ [15], PSPNet [16], and Deep Floor Plan (DFP) [1] on both R2V and R3D. ∗ denotes the result produced by our method with VGG-16 [38] backbone. Our method produces superior results in both datasets and has higher accuracy in almost all sub-classes. We did not report the m_IoU of Raster-to-Vector model since m_IoU metric is not conducted in their original paper [4] and the model’s relatively weak performance under accuracy metric implies that is has relatively low m_IoU.

![Diagram showing quantitative comparison results](image)

room. On the contrary, as shown in Fig 6 (c), our model is able to generate consistent and correct predictions with our Offset-Guided Attention Mechanism combined with Feature Fusion Attention module, no matter what the shape or size
of the room is. In the R3D dataset shown as Fig 7 (c, d), our results achieve superior room uniformity and consistency over Deep Floor Plan [1]. Quantitatively, according to Table 1, our model has higher accuracy for almost all sub-classes for both R2V and R3D datasets. Note that our approach is compatible with different backbone network architectures. Our results consistently outperform existing works with ResNet and VGG backbones, as shown in Table 1 “Ours” and “Ours*”.  

E. MORE RESULTS

We further proceed to analyze our network’s ability in various specific cases. We divide R3D floor plans into two types, irregular (first and third case) and rectangular (second and last case), and selected two cases of each type. As shown in Fig 8 (a, b), our model is able to produce highly accurate and unified room predictions in both situations, manifesting the ability of our network in handling rooms with different shapes. Besides, our model is able to recognize walls of different thicknesses accurately. As for the R2V dataset, it is mostly composed of rectangular floor plans, so we select the challenging cases that have complicated layouts and contain multiple rooms that look similar. Fig 8 (c, d) shows that our model can consistently generate precise and concrete predictions on all of them.  

V. ABLATION STUDY

A. OFFSET-GUIDED ATTENTION MODULE

First, we evaluate the effectiveness of Offset-Guided Attention module on floor plan recognition task. As shown in

![Figure 8](image-url)
Table 2 and Fig 10, all of the room categories attain inferior accuracy when the Offset-Guided Attention module is disabled, whereas the results of the boundary categories are not largely impacted. Notably, the performances of balcony, living room, and hall prediction decrease more significantly than the other categories since they are typically in either irregular shapes or have large areas. Our Offset-Guided Attention module helps to handle the irregular-shaped rooms by fusing the multiple predictions of the same room and improves the large-area room performance by increasing the network’s receptive field.

C. MORE ABLATION STUDIES

At last, we conduct additional evaluations on some designs of our proposed modules. To begin with, in the Offset-Guided Attention module, we study the effectiveness of the softmax normalization and the room-aware attention mechanism. Without the softmax normalization, the sum of attention values of all other pixels in the image to the target pixel is not necessarily to be 1, making the feature aggregation unstable. As shown in Table 3, the overall accuracy drops by 5% when softmax normalization is absent. To validate the effectiveness of the room-aware attention mechanism, we use an alternative attention mechanism based on the absolute distance between two pixels. As shown in Table 3 “Absolute Distance”, the overall accuracy has a 2% decrease when Offset-Guided Attention is replaced by absolute distance based attention, illustrating the superiority of our Offset-Guided room attention module.

Then, we evaluate several key components in our Feature Fusion Attention module, including the effectiveness of the Feature Fusion Attention module in each branch and average pooling. Table 4 shows results when a specific part is absent or altered. Notably, the absence of the Feature Fusion Attention module in either room or boundary branch results in the general performance drop in multiple sub-classes, implying that the FFA module only expresses its functionality when applied on both branches, since this module is designed to enhance the prediction consistency of the two branches. Max pooling layer yields comparable results as our network with average pooling, since both of the pooling strategies are able to extract a semantic-meaningful global feature from the feature map for the subsequent attention operations.

Lastly, we analyze the loss curve of our model by recording the loss at specified epochs. Fig 9 reveals that the loss curve exhibits a steady decline after the first 10 epochs. Moreover, the loss continues to decrease steadily up to epoch 100, indicating the potential for better performance with increased epochs. This experiment shows that our model steadily converges in the whole optimization process.
In this work, we present a novel method for floor plan recognition and reconstruction, a multi-task network with room-boundary-guided attention,” in Proc. IAPR Int. Workshop Document Anal. Syst., Mar. 2016.

VI. CONCLUSION

In this work, we present a novel method for floor plan recognition task that has the following contributions: first, we design an Offset-Guided Attention module to encourage the consistency of predictions within a single room; second, we design a Feature Fusion Attention module that further enhances the performance by enhancing the prediction consistency between room and boundary branches. Further, we extensively evaluate our approach on two commonly used datasets R2V and R3D. Qualitative and quantitative evaluations show the superiority of our network over the existing works on floor plan recognition. In the future, we will extend the work to more tasks and practical applications such as floor plan instance segmentation and 3D reconstruction, et.al.

REFERENCES

[1] Z. Zeng, X. Li, Y. K. Yu, and C. Fu, “Deep floor plan recognition using a multi-task network with room-boundary-guided attention,” in Proc. IEEE/CVF Int. Conf. Comput. Vis. (ICCV), Oct. 2019, pp. 9095–9103.
[2] S. Ahmed, M. Liwicki, M. Weber, and A. Dengel, “Improved automatic analysis of architectural floor plans,” in Proc. Int. Conf. Document Anal. Recognit. (ICDAR), Sep. 2011, pp. 864–869.
[3] X. Lv, S. Zhao, X. Yu, and B. Zhao, “Residential floor plan recognition and reconstruction,” in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2021, pp. 16712–16721, doi: 10.1109/CVPR46437.2021.01644.
[4] C. Liu, J. Wu, P. Kohli, and Y. Furukawa, “Raster-to-vector: Revisiting floorplan transformation,” in Proc. IEEE Int. Conf. Comput. Vis. (ICCV), Oct. 2017, pp. 2214–2222.
[5] S. Ahmed, M. Liwicki, M. Weber, and A. Dengel, “Automatic room detection and room labeling from architectural floor plans,” in Proc. 10th IAPR Int. Workshop Document Anal. Syst., Mar. 2012, pp. 339–343.
[6] C. Ahn-Soon and K. Tombre, “Variations on the analysis of architectural drawings,” in Proc. 4th Int. Conf. Document Anal. Recognit. (ICDAR), 1997, pp. 347–351.
[7] L. Gimenes, S. Robert, F. Suard, and K.-D. Zeick, “Automatic reconstruction of 3D building models from scanned 2D floor plans,” Autom. Constr., vol. 63, p. 486, Mar. 2016.
[8] D. Bahdanau, K. Cho, and Y. Bengio, “Neural machine translation by jointly learning to align and translate,” in Proc. Int. Conf. Learn. Represent., 2015, pp. 1–15.
[9] Z. Huang, X. Wang, Y. Wei, L. Huang, H. Shi, W. Liu, and T. S. Huang, “CCNet: Criss-cross attention for semantic segmentation,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 45, no. 6, pp. 6896–6908, Jun. 2023.
[10] C. Liu, A. G. Schwingle, K. Kundu, R. Urtasun, and S. Fidler, “Rent3D: Floor-plan priors for monocular layout estimation,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2015, pp. 3413–3421.
[11] S. Macê, H. Locteau, E. Valveny, and S. Tabbone, “A system to detect rooms in architectural floor plan images,” in Proc. 9th IAPR Int. Workshop Document Anal. Syst., Jun. 2010, pp. 9–11.
[12] E. Shellhammer, J. Long, and T. Darrell, “Fully convolutional networks for semantic segmentation,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 39, no. 4, pp. 640–651, Apr. 2017.
[13] O. Ronneberger, P. Fischer, and T. Brox, “Net: Convolutional networks for biomedical image segmentation,” in Proc. MICCAI, 2015, pp. 234–241.
[14] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2016, pp. 770–777.
[15] L.-C. Chen, Y. Zhu, G. Papandreou, F. Schroff, and H. Adam, “Encoder–decoder with atrous separable convolution for semantic image segmentation,” in Proc. Eur. Conf. Comput. Vis. (ECCV), 2018, pp. 833–851.
[16] H. Zhao, J. Shi, X. Qi, X. Wang, and J. Jia, “Pyramid scene parsing network,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Jul. 2017, pp. 6230–6239.
[17] J. Wang, K. Sun, T. Cheng, B. Jiang, C. Deng, Y. Zhao, D. Liu, Y. Mu, M. Tan, X. Wang, W. Liu, and B. Xiao, “Deep high-resolution representation learning for visual recognition,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 43, no. 10, pp. 3349–3364, Oct. 2021.
[18] L. Chen, G. Papandreou, I. Kokkinos, K. Murphy, and A. L. Yuille, “DeepLab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected CRFs,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 40, no. 4, pp. 834–848, Apr. 2018.
[19] F. Yu and V. Koltun, “Multi-scale context aggregation by dilated convolutions,” in Proc. Int. Conf. Learn. Represent. (ICLR), 2016, pp. 1–13.
[20] A. Paszke, A. Chaurasia, S. Kim, and E. Culurciello, “ENet: A deep neural network architecture for real-time semantic segmentation,” 2016, arXiv:1606.02147.
[21] X. Qi, Z. Liu, J. Shi, H. Zhao, and A. J. Jia, “Augmented feedback in semantic segmentation under image level supervision,” in Proc. Eur. Conf. Comput. Vis. (ECCV). Amsterdam, The Netherlands: Springer, 2016, pp. 90–105.
[22] V. Badrinarayanan, A. Kendall, and R. Cipolla, “SegNet: A deep convolutional encoder–decoder architecture for image segmentation,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 39, no. 12, pp. 2481–2495, Dec. 2017.
[23] H. Zhao, X. Qi, X. Shen, J. Shi, and J. Jia, “ICNet for real-time semantic segmentation on high-resolution images,” in Proc. Eur. Conf. Comput. Vis. (ECCV), 2018, pp. 405–420.
[24] H. Zhao, Y. Zhang, S. Liu, J. Shi, C. Loy, D. Lin, and J. Jia, “PSANet: Point-wise spatial attention network for scene parsing,” in Proc. Eur. Conf. Comput. Vis. (ECCV), 2018, pp. 267–283.
[25] Z. Liu, X. Qi, and C. Fu, “3D-to-2D distillation for indoor scene parsing,” in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2021, pp. 4462–4472.
[26] C. Zou, A. Colburn, Q. Shan, and D. Hoiem, “LayoutNet: Reconstructing the 3D room layout from a single RGB image,” in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2018, pp. 2051–2059.
[27] Y. Zhang, S. Song, P. Tan, and J. Xiao, “PanoContext: A whole-room 3D context model for panoramic scene understanding,” in Proc. Eur. Conf. Comput. Vis. (ECCV), 2014, pp. 668–686.
[28] S. Yang, F. Wang, C. Peng, P. Wonka, M. Sun, and H. Chu, “DuLaNet: A dual-projection network for estimating room layouts from a single RGB panorama,” in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2019, pp. 3358–3367.
[29] T. Yamasaki, J. Zhang, and Y. Takada, “Apartment structure estimation using fully convolutional networks and graph model,” in Proc. ACM Workshop Multimedia Real Estate Tech., Jun. 2018, pp. 1–6.
[30] Z. Liu, X. Qi, and C. Fu, “One thing one click: A self-training approach for weakly supervised 3D semantic segmentation,” in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2021, pp. 1726–1736.

[31] E. Xie, W. Wang, Z. Yu, A. Anandkumar, J. M. Alvarez, and P. Luo, “SegFormer: Simple and efficient design for semantic segmentation with transformers,” in Proc. Adv. Neural Inf. Process. Syst., vol. 34, 2021, pp. 12077–12090.

[32] B. Cheng, A. Schwing, and A. Kirillov, “Per-pixel classification is not all you need for semantic segmentation,” in Proc. Adv. Neural Inf. Process. Syst., vol. 34, 2021, pp. 17864–17875.

[33] F. Boniardi, A. Valada, R. Mohan, T. Caselitz, and W. Burgard, “Robot localization in floor plans using a room layout edge extraction network,” in Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS), Nov. 2019, pp. 5291–5297.

[34] G. Gerstweiler, L. Furlan, M. Timofeev, and H. Kaufmann, “Extraction of structural and semantic data from 2D floor plans for interactive and immersive VR real estate exploration,” Technologies, vol. 6, no. 4, p. 101, 2018.

[35] S. C. Kwok-Fung, G. Baciu, and H. Sun, “Reconstruction of 3D virtual buildings from 2D architectural floor plans,” in Proc. VRST, 1998, pp. 17–23.

[36] R. Geirhos, P. Rubisch, C. Michaelis, M. Bethge, A. F. Wichmann, and W. Brendel, “ImageNet-trained CNNs are biased towards texture; increasing shape bias improves accuracy and robustness,” in Proc. Int. Conf. Learn. Represent. (ICLR), 2019, pp. 1–22.

[37] J. Hu, L. Shen, and G. Sun, “Squeeze-and-Excitation networks,” in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit., Jun. 2018, pp. 7132–7141, doi: 10.1109/CVPR.2018.00745.

[38] K. Simonyan and A. Zisserman, “Very deep convolutional networks for large-scale image recognition,” 2014, arXiv:1409.1556.