More Diverse Means Better: Multimodal Deep Learning Meets Remote Sensing Imagery Classification

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Abstract—This is the pre-acceptance version, to read the final version please go to IEEE Transactions on Geoscience and Remote Sensing on IEEE Xplore. Classification and identification of the materials lying over or beneath the Earth’s surface have long been a fundamental but challenging research topic in geoscience and remote sensing (RS) and have garnered a growing concern owing to the recent advancements of deep learning techniques. Although deep networks have been successfully applied in single-modality-dominated classification tasks, yet their performance inevitably meets the bottleneck in complex scenes that need to be finely classified, due to the limitation of information diversity. In this work, we provide a baseline solution to the aforementioned difficulty by developing a general multimodal deep learning (MDL) framework. In particular, we also investigate a special case of multi-modality learning (MML) – cross-modality learning (CML) that exists widely in RS image classification applications. By focusing on “what”, “where”, and “how” to fuse, we show different fusion strategies as well as how to train deep networks and build the network architecture. Specifically, five fusion architectures are introduced and developed, further being unified in our MDL framework. More significantly, our framework is not only limited to pixel-wise classification tasks but also applicable to spatial information modeling with convolutional neural networks (CNNS). To validate the effectiveness and superiority of the MDL framework, extensive experiments related to the settings of MML and CML are conducted on two different multimodal RS datasets. Furthermore, the codes and datasets will be available at: https://github.com/danfenghong/IEEE_TGRS_MDL-RS.

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Fig. 1. A multimodal example (Berlin) for RS imagery classification, where four data sources, i.e., HS, MS, SAR, and OSM, are available in a same scene. Contributing to the RS community.

Index Terms—Classification, CNNs, cross modality, deep learning, feature learning, fusion, hyperspectral, lidar, multimodal, multispectral, network architecture, remote sensing, SAR.

I. INTRODUCTION

Beyond any doubt, remotely sensed image classification or mapping [1]–[8], i.e., land use and land cover (LULC), plays an increasingly significant role in earth observation (EO) missions, as many high-level applications, to a great extent, depend on classification products, such as urban development and planning, forest monitoring, soil composition analysis, disaster response and management, to name a few.

Over the past decades, enormous effects have been made to extract discriminative features and design efficient classifiers for remote sensing (RS) data classification. However, most of these classification techniques, either unsupervised or supervised, are merely designed and applied for single modalities, e.g., hyperspectral (HS) [9], multispectral (MS) [10], light detection and ranging (LiDAR) [11], synthetic aperture radar (SAR) [12], OpenStreetMap (OSM), etc. The ability in identifying materials on the surface of the Earth, therefore, remains limited, due to the lack of rich and diverse information, particularly in challenging scenes where certain categories are similar and cannot be accurately classified by only single modalities. For instance, in urban planning, the structure types of surface materials are hardly identified using only one modality information (e.g., spectral data) [13]. There are no big differences in spectral profiles between the “grass” on the ground and the “grass” on the roof, but they can be well separated by means of height information obtained from
In object detection and localization (e.g., cars), the HS data is characterized by more discriminative spectral properties, while the RGB or MS products are capable of providing richer and finer spatial information [15]. This is also a typical win-win case. Moreover, it is well known that optical RS images suffer from the effects of cloud coverage in image acquisition, leading to partial information missing. SAR can be seen as an auxiliary data source to address the issue effectively, due to its different imaging mechanism and sensors that are able to penetrate the cloud [16].

Different imaging technologies in RS are capable of capturing a variety of properties from the Earth’s surface, such as spectral radiance and reflectance, height information, texture structure, and spatial characteristics. The joint exploitation of multiple modalities enables us to characterize the scene at a more detailed and precise level unachievable by using single modality data [17]. In addition, a large amount of multimodal earth observation data, such SAR, MS, HS, and digital surface model (DSM), become openly available from currently operational spaceborne radar (e.g., Sentinel-1), optical broadband (e.g., Sentinel-2, Landsat-8), and imaging spectroscopy (e.g., Hyperion, DESIS, Gaofen-5) missions as well as various airborne sensors (e.g., HyMap, HySpex) or laser scanning [18]. Fig. 1 shows a classification example with multimodal RS data. This further motivates us to investigate and design advanced multimodal data analysis (MDA) techniques. Despite many conventional MDA-related approaches proposed and used by attempts to enhance the classification results of RS data sources, yet the relatively poor capability of these models in data representation limit the performance gain [19]–[22]. Inspired by the recent success of deep learning (DL), some preliminary studies [23]–[26] have addressed this issue with the multimodal input. Their outcomes, to some extent, have shown a great potential in RS imagery classification tasks.

Nevertheless, there still lacks a unified MDA-targeted DL architecture that is able to clarify three open questions, that is, “what to fuse”, “how to fuse”, and “where to fuse”. To this end, we propose a general multimodal DL framework for the RS imagery classification. The proposed model aims to provide an inclusive baseline network to break the bottleneck of classification performance under the conditions of using single modalities, where several fusion modules can be well embedded. Furthermore, extensive experiments conducted on three different multi-modal datasets freely available demonstrate the MDL-RS’s superiority in terms of either the common multi-modality learning (MML) or the special cross-modality learning (CML) issue (see Fig. 2) using the fully connected (FC) networks (FC-Nets for short) and convolutional neural networks (CNNs). The main contributions in this paper can be highlighted as follows.

- We propose a unified multimodal DL framework with a focus on the RS image classification, MDL-RS for short, which assembles pixel-level labeling guided by an FC design and spatial-spectral joint classification with CNNs-dominated architecture.
- The proposed MDL-RS is not only applicable to the case of MML, but also able to be generalized to CML’s with more effective and compact modality blending.
- Five plug-and-play fusion modules are investigated and devised in the MDL-RS networks. They are early fusion, middle fusion, late fusion, encoder-decoder (En-De) fusion, and cross fusion, where the first four approaches are the well-known fusion strategy yet lack of being generalized in a unified framework, and the last one is a newly-proposed contribution that can transfer the information across modalities more effectively.

Fig. 2 briefly illustrates the MML and CML for training and testing. Accordingly, we will highlight some significant works related to the two topics in the following.

### A. Shallow Models for MML

Many classic shallow models related to MML, i.e., morphological operators and subspace learning, have been successfully employed for feature extraction and classification of multimodal RS observations. For example, Liao et al. [19] proposed to fuse the morphological profiles (MPs) of HS and LiDAR data on manifolds by means of graph-based subspace learning. Similarly, Ref. [20] extracted the attribute profiles (APs) instead of MPs used in [19] for land-cover classification. In [27], extinction profiles (EPs) combined with total variation component analysis are used for the fusion of
HS and LiDAR. The fusion work is improved in [28] by jointly using sparse and low-rank subspace modeling. Yokoya et al. [21] simply stacked multiple features obtained from MS and OpenStreetMap data before feeding into the classifier for local climate zones (LCZ) classification. Supported by topological theory, Hu et al. [29] developed an MAPPER-based manifold alignment technique by extending [30] for the semi-supervised fusion of HS and polarimetric SAR images. Besides, some follow-up researches [31]–[35] have been successively proposed by the attempts to enhance the capability of information blending between multi-modalities with more advanced strategies.

B. Deep Models for MML

Due to its finer and richer characterization of the scene, DL techniques [35] have made great progress on multimodal image analysis and understanding. In recent years, researchers have sought to explore possibilities of using MDL and developing its variants for classifying multimodal RS images more effectively. These models can be roughly categorized into two groups.

One is the common pixel-level multimodal classification network. Typically, Ghamisi et al. [36] extracted the EPs from HS and LiDAR data and fused them on the deep feature space generated by deep CNNs. Further, Chen et al. [23] designed a end-to-end deep fusion network, which consists of two CNNs for feature extraction and one DNN for feature fusion. In [24], authors put forward to use the two-branch CNNs with cascade blocks for automatic feature extraction and fusion of multisource RS data. A general DL-based framework is developed in [25] for the fusion of multitemporal and multimodal satellite data. The other MDL-based family aims to assign a semantic category to each pixel in the object-level fashion, also known as semantic segmentation (SS). A representative model proposed by Audebert et al. [37] is to segment multimodal EO data – high-resolution RGB and DSM images – using a multi-scaled network design. The same researchers further extended their model with two kinds of fusion strategies: early fusion and late fusion [38]. Another interesting work [39] derives from a geographically-regularized deep multi-task networks for SS in aerial images. Srivastava et al. [40] provided an MDL’s solution to enhance the understanding of urban land use from both overhead and ground images. Lately, the winners in 2018 IEEE Data Fusion Contest (DFC) reported their SS results via a fused fully convolutional network (FCN) conducted on MS-LiDAR and HS data [41]. It should be noted, however, that segmentation networks usually rely on abundant labeled images and high-resolution data sources. This not only poses a great challenge in saving time and cost, but also is relatively difficult to classify accurately with small samples. Thus, this paper mainly bends our efforts for pixel-level classification tasks of multimodal RS images.

C. CML: A Special Case of MML

As a special family of MML, CML aims to train a model that is able to achieve a same or closer performance using either a certain modality or multiple modalities as the input during inference process, as illustrated in Fig. 2(c). Very recently, there has been an increasing attention on the study related to CML. Sun et al. [42] made an attempt at spectrally enhancing MS imagery with partially overlapped HS data. The proposed method is a simple but feasible solution to the CML’s issue. A similar work was also presented in [43] to investigate the impact of spectral enhancement on soil erosion by unmixing-based evaluation. Another stream for this topic is to directly perform feature-level learning instead of image or spectrum-based evaluation. Volpi et al. [44] employed the kernelized canonical correlation analysis (KCCA) to measure the dependencies between cross-sensor images for the change detection task. Hong et al. [45], [46] learned a common subspace from a small overlapped area of HS and MS images. The subspace can be regarded as a “bridge” to connect the two modalities and transfer more diverse information from one to another more effectively, particularly for larger-coverage mapping. Beyond supervision, Hong et al. [47] further extended their model to a semi-supervised version by learning a graph structure for alignment of labeled and unlabeled samples. We observed that data acquisition on a large scale remains challenging with an emphasis to the need of aligned multimodal sources. As compared to the case of MML, boosting the development of CML is therefore becoming more deserving in practical RS applications, e.g., large-scale classification. Yet it is relatively
less investigated by RS researchers, especially in DL-guided classification tasks.

III. METHODOLOGY

A. Method Overview

We aim at developing a generic end-to-end multimodal deep network for RS imagery classification. The MDL-RS is shaped in the two different forms: pixel-wise and spatial-spectral architectures designed by FC-Nets and CNNs. Further, the two versions are both composed of two key modules with a focus on feature representation learning of multimodal data: Extraction Network (Ex-Net) and Fusion Network (Fu-Net). Fig. 3 illustrates a general overview of the MDL-RS framework. Intuitively, the proposed MDL-RS jointly trains two subnetworks (Ex-Net and Fu-Net) in an end-to-end fashion.

B. Extraction Network (Ex-Net)

Our MDL-RS starts with a feature extraction network, that is Ex-Net, which extracts hierarchical representations from different modalities. These extracted features (on the feature space) enable better information blending, particularly heterogeneous data (e.g., from different sensors) which usually fail to be fused well on the original space.

Let $X_1 \in \mathbb{R}^{d_1 \times N}$ and $X_2 \in \mathbb{R}^{d_2 \times N}$ be different modalities with $d_1$ and $d_2$ dimensions, respectively, by $N$ pixels, where $x_{1,i}$ and $x_{2,i}$ denote as an aligned $i$-th pixel-pair. The two modalities share the same label information, denoted as $Y \in \mathbb{R}^{C \times N}$ with $C$ categories by $N$ pixels, which is a one-hot encoded label matrix. With these definitions, the output in the $l$-th layer of Ex-Net can be then written as

\[
z_{s,i}^{(l)} = \begin{cases} h_{W_s^{(l)}, b_s^{(l)}}(x_{s,i}), & l = 1, \\ h_{W_s^{(l)}, b_s^{(l)}}(z_{s,i}^{(l-1)}), & l = 2, \ldots, p, \end{cases}
\]

where $s = 0, 1, 2$ denotes different network streams, in particular, $s = 1, 2$ for different modalities and $s = 0$ for the fusion stream. Here, $h(\cdot)$ is defined as the linear regression function (e.g., encoder or convolutional operation) with respect to the to-be-learned weights $\{W_s^{(l)}\}_{l=1}^p$ and biases $\{b_s^{(l)}\}_{l=1}^p$ of all layers ($l = 1, 2, \ldots, p$) in the Ex-Net. Inspired by the success of a batch normalization (BN) operation [48] that can speed up the network convergence and alleviate the problems of exploding or vanishing gradients by reducing the internal covariance shift between samples, a BN layer is then added over the output $z_{s,i}^{(l)}$.

\[
z_{BN,s,i}^{(l)} = \gamma_s z_{s,i}^{(l)} + \beta_s,
\]

where $\hat{z}_{s,i}^{(l)}$ is the $z$-score result of $z_{s,i}^{(l)}$, $\gamma_s$ and $\beta_s$ denote the learnable network parameters for the $s$-th network (or modality) stream. Before importing the $z_{BN,s,i}^{(l)}$ into the next block\(^1\), we have the following output ($a_{s,i}^{(l)}$) behind an nonlinear activation function

\[
a_{s,i}^{(l)} = u(z_{BN,s,i}^{(l)}).
\]

Here, $u(\cdot)$ is defined as the nonlinear activation function, which is performed by ReLU, i.e.,

\[
u(\cdot) = \max(0, \cdot).
\]

C. Fusion Network (Fu-Net)

Once the input modalities $X_1$ and $X_2$ pass through the Ex-Net, their encoded features, denoted as $\{A_s = [a_{s,1}^{(p)}, \ldots, a_{s,N}^{(p)}]\}_{s=1}^2$, can be regarded as the new input and fed into the Fu-Net in an end-to-end fashion. Using a similar block

\(^1\)We define the sequence of encoder (or convolution) operation, BN, and nonlinear activation as a block in networks.
of Ex-Net, e.g., Eqs. (1) to (3), the output of Fu-Net can be
generalized to
\[ a_i^{(l)} = f_{W_i^{(l)}, b_i^{(l)}}(a_{i-1}^{(p)}), \quad l = p + 1, \ldots, q, \]  
(5)
where \( f(\cdot) \) denotes the nonlinear mapping function that
consists of several blocks in the Fu-Net. By investigating “how to
fuse”, we will unfold the Fu-Net in our MDL-RS framework
for the following two groups.

1) Concatenation-based fusion: An intuitive fusion way in
Fu-Net is to simply stack the outputs derived from the different
streams in networks. According to the requirement of “where
to fuse”, the fusion manner can be further categorized into
different fusion representation [49, 50], as shown in Figs. 4(a)–4(c). Hence, the vector representation \( v_i \) in the
\( i \)-th pixel corresponding to the aforementioned three fusion
strategies are successively written as
\[ v_i = \begin{cases} a_i^{(l)}, & l = p, \\ [f_{W_i^{(l)}, b_i^{(l)}}(a_i^{(p)}), f_{W_{i+1}^{(l)}, b_{i+1}^{(l)}}(a_{i+1}^{(p)})], & p < l < q, \\ [f_{W_i^{(l)}, b_i^{(l)}}(a_i^{(p)}), f_{W_{i+1}^{(l)}, b_{i+1}^{(l)}}(a_{i+1}^{(p)})], & l = q, \end{cases} \]  
(6)
where \( \forall l \in \mathbb{Z} \) (integer set), and “\([\cdot, \cdot]\)” denotes the usual
concatenation.

2) Compactness-based fusion: Fu-Net aims to learn better
features over multiple modalities. Although the widely-used
concatenation-based fusion has shown its success in feature
extraction and representation, yet the capability in blending
different properties, especially for heterogeneous data, re-
mains limited. Alternatively, a feasible solution is to fuse the
features of different modalities in a more compact way.

One representative approach presented in [51] is the En-De
fusion (see Fig. 4(d) for details), which can be performed by
minimizing the following reconstruction loss
\[ \min_{\phi, \varphi} \sum_{s=1}^{2} \| X_s - g_{\varphi}(f_{\phi}(X_s)) \|_F^2, \]  
(7)
where \( f_{\phi}(X_s) \) is the frobenius norm, and \( f_{\phi}(\cdot) \) and \( g_{\varphi}(\cdot) \) are defined as
the encoder and the reconstruction-based decoder with respect to
to the to-be-estimated variable sets \( \phi := \{ W_s^{(l)}, b_s^{(l)} \}_{l=1}^p \) and
\( \varphi := \{ \tilde{W}_s^{(l)}, \tilde{b}_s^{(l)} \}_{l=1}^p \), respectively.

Another plug-and-play fusion module proposed in this paper
is named as cross fusion. As the name suggests, the module
seeks to learn more compact feature representations across
modalities by interactively updating the parameters of different
subnetworks. Owing to such a setting, the network stream
for one modality is capable of not only learning the specific
properties from itself but also considering more diversified
supplement from another stream towards a more sufficient
information blending. Taking the \( i \)-th pixel as an example, the
fusion representation then is
\[ a_i^{(l)} = f_{W_i^{(l)}, b_i^{(l)}}(a_i^{(p)}), \quad \frac{1}{a_i^{(l)}} = f_{W_{i+1}^{(l)}, b_{i+1}^{(l)}}(a_{i+1}^{(p)})], \]  
(8)
where the three components (each row of the matrix) of
\( v_i \) in Eq. (8) share the same to-be-learned parameters. In
other words, they can be also seen as three “new” different
samples for the input of the next layer to enforce a more
compact fusion. Fig. 4(e) illustrates the interactive process in
networks, where highly compact fusion via crossing weights
and features enables “better” and “more effective” fusion
representations. More specifically, the learned weights are used
across modalities, e.g., the weights learned from modality A
might be simultaneously acted on modality B and vice versa.
Then, the features after summation or concatenation with
cross combination of features again are output as the final
fusion representations of cross fusion (please see Fig. 4(e) and
Eq. (8) for more details).

D. Significance of Compact Blending in CML

Up to the present, a large amount of EO data, e.g., MS,
SAR, have been freely available, thus making it possible to
yield a large-scale and even global scale mapping (or clas-
sification). Despite so, the data with richer spatial information,
such as HS images, are hardly acquired on a large scale, due
to the costly storage and limitations of imaging techniques. In
this connection, CML may be an effective solution to break
the performance bottleneck of current models in classification accuracy by learning better feature representations over multiple source data during model training.

We found, however, that massive connections in the concatenation-based fusion module occur in variables from the same modality but few neurons across the modalities are activated, even if each modality passes through individual Ex-Net before being fed into the fusion layer. As illustrated in Fig. 5(a), it is obvious that the neurons from one modality are activated, even if each modality passes through individual Ex-Net. Unlike early fusion before feature extraction is a single-stream network for either Ex-Net or Fu-Net, middle fusion, late fusion, en-de fusion, and cross fusion in the MDL-RS framework follow a two-stream Ex-Net.

The fusion behavior happens in the input for early fusion, the Block 5 of Fu-Net for middle fusion, en-de fusion, and cross fusion, and the Block 7 of Fu-Net for late fusion.

Unlike middle fusion, late fusion, and cross fusion that hold the same setting for each layer in Fu-Net, en-de fusion needs to learn additional network parameters to reconstruct the fused features generated from Block 4 of Fu-Net. The reconstruction module consists of the similar blocks with Ex-Net by removing BN layer and replacing ReLU with Sigmoid.

E. Network Architecture for MDL-RS

As we mentioned, the proposed MDL-RS framework aims to provide a baseline network for multimodal RS imagery classification, and many plug-and-play modules can be embedded into the networks. For this purpose, we empirically and experimentally set up a basic network architecture of the MDL-RS, including two versions: pixel-wise FC-Nets and spatial-spectral CNNs, and detail them in a layer-by-layer manner. Table I lists configuration for the layer-wise network architecture. Note that there are slight differences between different fusion modules in the basic architecture, which are detailed as below.

- Our MDL-RS framework for single modalities and early fusion before feature extraction is a single-stream network for either Ex-Net or Fu-Net.
- Middle fusion, late fusion, en-de fusion, and cross fusion in the MDL-RS framework follow a two-stream Ex-Net.
- The fusion behavior happens in the input for early fusion, the Block 5 of Fu-Net for middle fusion, en-de fusion, and cross fusion, and the Block 7 of Fu-Net for late fusion.

IV. EXPERIMENTS

A. Data Description

In the experiments, two multimodal datasets, including HS-LiDAR and MS-SAR data, are used for performance assessment both quantitatively and qualitatively. A brief description for the two datasets is given as follows.

1) HS-LiDAR Houston2013 data: The HS product was acquired by the ITRES CASI-1500 imaging sensor over the campus of University of Houston and its surrounding rural areas in Texas, USA, which was released for the IEEE GRSS
TABLE III
A LIST OF THE NUMBER OF TRAINING AND TESTING SAMPLES FOR EACH CLASS IN LCZ DATASETS.

| No. | Class Name      | Training (Berlin) | Testing (Hong Kong) |
|-----|-----------------|-------------------|---------------------|
| 1   | Compact Mid-rise| 1534              | 179                 |
| 2   | Open High-rise  | 577               | 673                 |
| 3   | Open Mid-rise   | 2448              | 126                 |
| 4   | Open Low-rise   | 4010              | 120                 |
| 5   | Large Low-rise  | 1654              | 137                 |
| 6   | Dense Trees     | 4960              | 1616                |
| 7   | Scattered Trees | 1028              | 540                 |
| 8   | Bush and Scrub  | 1050              | 691                 |
| 9   | Low Plants      | 4424              | 985                 |
| 10  | Water           | 1732              | 1603                |
|     | Total           | 23417             | 7670                |

DFC2013². The datasets consist of two data sources with 144 bands covering the wavelength range from 364nm to 1046nm at a 10nm spectral interval for HS image and 1 band for LiDAR data, by $349 \times 1905$ pixels. Moreover, 15 LULC-related categories are investigated in the scene, whose details in terms of the class names and the size of training and testing sets are listed in Table II, while Fig. 6 shows false-color images of the studied scene and the distributions of training and testing samples applied for the classification task.

2) MS-SAR LCZ data: The LCZ datasets are collected from Sentinel-2 and Sentinel-1 satellites, where the former acquires the MS data with 10 spectral bands and the latter is able to generate the dual-polarimetric SAR data organized as a common-used PolSAR covariance matrix (four components) [32]. To avoid the information leak in evaluating the classification performance of the models, we thoroughly separate the training and testing sets in the LCZ datasets by training the networks on the area of Berlin and inferring the models on Hong Kong and its surroundings. Please note that the labeled ground truth for the two cities and the Sentinel-2 MS data are available from the IEEE GRSS DFC2017³, as detailed in Table III and visualized in Fig. 8.

B. Experimental Setup

1) Implementation details: The proposed networks are implemented on the Tensorflow platform. These models are trained on the training set, and the hyper-parameters are determined using a grid search on the validation set. More specifically, ten replications are performed to randomly separate the original training set into the new training set and validation set with the percentage of 8:2 for the final network’s hyper-parameters. In the training phase, we adopt the Adam optimizer with the “exponential” learning rate policy. The current learning rate can be updated by multiplying the base one with $(1 - \frac{\text{iter}}{\text{maxIter}})^{\text{power}}$ at intervals of 30 epochs, where the initialized learning rate and power are set to 0.001 and 0.5, respectively. We initialize the subnetworks for each modality with He initialization [53]. Due to the randomness in initialization, the averaged results will be reported out of ten runs. Moreover, the momentum is parameterized by 0.9, and the training batch is set to 64 and 256 in the first and second datasets, respectively. To facilitate network training and reduce overfitting, we also employ the $\ell_2$-norm regularization on weights to avoid overfitting problems. The networks would stop training when the validation loss fails to decrease.

2) Evaluation metric: Pixel-level RS image classification is explored as a potential target for evaluating the performance of the proposed MDL-RS framework. More specifically, three commonly-used indices – Overall Accuracy (OA), Average Accuracy (AA), and Kappa Coefficient ($\kappa$) – are calculated to quantify classification performance. They can be formulated by using the following equations.

\[
OA = \frac{N_c}{N_a},
\]

\[
AA = \frac{1}{C} \sum_{i=1}^{C} \frac{N^i_c}{N^i_a},
\]

and

\[
\kappa = \frac{OA - P_c}{1 - P_c},
\]

where $N_c$ and $N_a$ denote the number of samples classified correctly and the number of total samples, respectively, while $N^i_c$ and $N^i_a$ correspond to the $N_c$ and $N_a$ of each class, respectively. $P_c$ in $\kappa$ is defined as the hypothetical probability of chance agreement [55], which can be computed by

\[
P_c = \frac{N^1_c \times N^1_a + \ldots + N^i_c \times N^i_a + \ldots + N^C_c \times N^C_a}{N_a \times N_a},
\]

where $N^i_c$ and $N^i_a$ denote the number of real samples for each class and the number of predicted samples for each class, respectively.

3) Comparison with state-of-the-art baselines: Several state-of-the-art baselines in terms of different fusion strategies are selected for comparison, including concatenation-based fusion: early fusion, middle fusion, and late fusion, and compactness-based fusion: en-de fusion and cross fusion, as well as single modalities. These models are also performed by using both FC-Nets and CNNs frameworks. It is worth noting, however, that the patch centered by a pixel is usually used as the input of CNNs in RS image classification. For this reason, we need to extend the original image by the “replicate” operation, that is, copying the pixels within the image to that out of the original image boundary, to solve the problem of the boundaries of the multimodal RS data in the CNNs-related experiments.

²http://www.grss-ieee.org/community/technical-committees/data-fusion/2013-ieee-grss-data-fusion-contest/
³http://www.grss-ieee.org/2017-ieee-grss-data-fusion-contest/
TABLE IV

| Method       | C1      | C2      | C3      | C4      | C5      | C6      | C7      | C8      | C9      | C10     | C11     | C12     | C13     | C14     | C15     | OA      | AA      | κ       |
|--------------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|
| MML          |         |         |         |         |         |         |         |         |         |         |         |         |         |         |         |         |         |         |
| HSI          | 82.72   | 83.36   | 100.05  | 92.05   | 98.20   | 95.10   | 82.84   | 48.53   | 74.88   | 52.80   | 80.74   | 84.25   | 75.79   | 100.00  | 98.77   | 80.39   | 33.33   | 78.83   |
| LiDAR        | 35.71   | 57.33   | 83.56   | 72.16   | 70.08   | 71.33   | 72.29   | 47.88   | 79.40   | 70.14   | 79.70   | 74.36   | 70.53   | 85.83   | 41.23   | 63.31   | 65.38   | 50.09   |
| Early        | 80.44   | 80.73   | 100.05  | 96.50   | 98.67   | 93.22   | 82.74   | 82.24   | 75.92   | 70.14   | 74.82   | 79.54   | 82.46   | 80.00   | 98.52   | 84.88   | 86.45   | 83.66   |
| Middle       | 82.84   | 84.21   | 99.05   | 96.80   | 98.80   | 99.38   | 98.80   | 89.80   | 83.57   | 81.87   | 79.75   | 87.95   | 80.46   | 95.82   | 86.62   | 88.58   | 85.56   |
| Late         | 81.58   | 83.65   | 100.05  | 93.09   | 99.90   | 91.50   | 82.65   | 81.29   | 88.29   | 89.00   | 83.78   | 90.39   | 82.46   | 98.10   | 88.52   | 89.95   | 87.59   |
| En-De        | 81.30   | 81.58   | 100.05  | 99.72   | 99.81   | 95.10   | 90.02   | 87.94   | 81.59   | 86.68   | 89.37   | 85.69   | 83.16   | 99.83   | 89.60   | 90.83   | 87.59   |
| Cross        |         |         |         |         |         |         |         |         |         |         |         |         |         |         |         |         |         |         |

| TABLE V

| Method       | C1      | C2      | C3      | C4      | C5      | C6      | C7      | C8      | C9      | C10     | C11     | C12     | C13     | C14     | C15     | OA      | AA      | κ       |
|--------------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|
| MML          |         |         |         |         |         |         |         |         |         |         |         |         |         |         |         |         |         |         |
| HSI          | 80.39   | 84.84   | 85.26   | 91.29   | 96.88   | 96.50   | 58.49   | 44.63   | 55.15   | 53.86   | 69.26   | 66.76   | 64.21   | 98.38   | 95.56   | 73.26   | 76.61   | 71.10   |
| LiDAR        | 85.78   | 85.20   | 99.60   | 88.73   | 95.05   | 91.50   | 91.14   | 47.77   | 76.78   | 79.73   | 83.02   | 84.05   | 74.04   | 100.00  | 98.52   | 82.53   | 84.91   | 81.11   |
| Early        | 68.76   | 84.02   | 51.39   | 99.09   | 88.18   | 62.25   | 16.24   | 12.64   | 57.69   | 24.69   | 96.47   | 83.40   | 98.52   | 40.98   | 39.40   | 36.84   |
| Middle       | 81.48   | 84.21   | 25.15   | 34.38   | 99.62   | 95.10   | 92.10   | 4.51    | 51.99   | 38.61   | 69.17   | 60.33   | 44.56   | 93.07   | 59.07   | 62.82   | 56.00   |
| Late         | 82.34   | 84.21   | 99.65   | 87.03   | 98.90   | 99.80   | 94.23   | 35.90   | 91.37   | 63.47   | 76.85   | 91.23   | 99.73   | 68.94   | 73.37   | 66.51   |
| En-De        | 96.39   | 78.20   | 85.36   | 91.29   | 96.88   | 96.50   | 58.49   | 44.63   | 55.15   | 53.86   | 69.26   | 66.76   | 64.21   | 98.38   | 95.56   | 73.26   | 76.61   | 71.10   |
| Cross        | 82.91   | 83.27   | 99.60   | 88.73   | 95.05   | 91.50   | 91.14   | 47.77   | 76.78   | 79.73   | 83.02   | 84.05   | 74.04   | 100.00  | 98.52   | 82.53   | 84.91   | 81.11   |

C. Result and Analysis on Houston Data

1) Quantitative comparison: Table IV lists the quantitative performance comparison in terms of OA, AA, and κ as well as the accuracy for each category using a FC-based feature extractor (see FC-Nets) in three different experimental setting, e.g., MML, CML-HSI, and CML-LiDAR.

Characterized by rich spectral information, single HSI performs better than single LiDAR (over 15% OA), even though APs are pre-extracted from the LiDAR image before feeding into the networks. Limited by feature diversity, the single modalities yield relatively poor performance compared to those with multimodal input in MML. Moreover, the classification performance of compactness-based approaches is generally superior to that of concatenation-based ones, bringing increments of at least 1% OA, AA, and κ. In details, late fusion and middle fusion are more effective than early fusion, while cross fusion outperforms others, achieving best classification results.

Regarding the CML’s case, due to missing one modality in the inference process, those concatenation-based fusion approaches basically fail to work well, particularly early fusion whose classification performance decreases dramatically to 28.13% OA in CML-HSI and 12.76% OA in CML-LiDAR. Although other two strategies seem to be acceptable to some extent, yet their results are even lower than those using single modalities. This might indicate that the above methods are
not feasible to the CML’s issue in practical applications. By contrast, the compactness-based cross fusion overcomes other competitors either in MML’s or in CML’s task. More significantly, the resulting model trained by cross fusion is capable of transferring the information from one modality to another one more effectively, yielding a higher classification accuracy than that using single modalities. In addition, the compactness-based fusion networks also behaves superiorly compared to the concatenation-based models from the perspective of per-class performance.
Furthermore, Table VI shows the corresponding results obtained by CNNs. Overall, these models with the CNNs-based architecture hold a higher-level classification performance compared to those with FC-Nets (cf. Table IV). The classification accuracies for all compared algorithms increase by 2% ∼ 3% in terms of three main indices as a whole. The benefits of the CNNs-based network design are, on the one hand, to extract the semantically meaningful information from locally neighboring pixels; and, on the other hand, able to generate more realistic classification maps.

2) Visual comparison: Figs. 6 and 7 visualize the classification maps of different networks for FC-Nets and CNNs, respectively, from which we have the following observations:

- The MDL can provide a better solution than single modalities to reduce the errors in semantic labeling. Moreover, the compactness-based fusion approaches tend to generate more realistic classification maps.
- CNNs are able to achieve smoother inference results compared to FC-Nets by removing noisy pixels in classification maps.
- Multimodal data fusion is conducive to provide robust solutions against spectral variabilities, i.e., cloud cover in optical imaging, and alleviate the performance degradation by the means of other data sources (e.g., LiDAR).
- Cross fusion module is capable of seeking out important information by the means of other data sources (e.g., LiDAR).

### Table VI
Quantitative comparison of different methods using FC-Nets on the MS-SAR datasets. The best is shown in bold.

| Method | C1  | C2  | C3  | C4  | C5  | C6  | C7  | C8  | C9  | C10 | OA   | AA   | κ   |
|--------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|------|-----|
| MSI    | 3.91| 5.2 | 21.41| 2.3 | 74.45| 89.23| 62.96| 14.47| 7.72 | 42.22| 42.13| 32.41| 33.00|
| SAR    | 4.15| 2.38| 8.03 | 2.92| 99.62| 34.05| 11.19| 0.98 |
| Early  | 8.94 | 17.46| 10.00| 78.10| 94.37| 53.52| 7.24 | 14.11| 51.71| 45.71| 33.54| 36.59|
| Middle | 9.5  | 17.46| 19.17| 78.83| 96.53| 30.56| 25.04| 8.73 | 53.55| 46.26| 33.94| 36.73|
| Late   | 0.56 | 0.15| 6.35  | 78.10| 10.15| 53.70| 16.06| 54.11| 90.66| 46.61| 30.99| 36.03|
| En-De  | 3.91 | 0.59| 6.35  | 74.45| 40.90| 6.85 | 58.07| 98.23| 51.47| 28.94| 40.11|
| Cross  | 7.82 | 54.76| 0.83  | 72.26| 59.90| 24.63| 18.38| 30.96| 94.89| 54.58| 36.44| 43.97|

### Table VII
Quantitative comparison of different methods using CNNs on the MS-SAR datasets. The best is shown in bold.

| Method | C1  | C2  | C3  | C4  | C5  | C6  | C7  | C8  | C9  | C10 | OA   | AA   | κ   |
|--------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|------|-----|
| MSI    | 1.12| 17.46| 9.17 | 91.97| 79.89| 72.96| 8.54 | 11.78| 55.28| 45.11| 34.82| 36.13|
| SAR    | 92.18| 38.10| 39.17| 9.49 | 22.09| 2.41 | 0.14 | 21.52| 85.67| 40.23| 31.08| 29.12|
| Early  | 10.61| 2.23 | 15.08| 0.83 | 83.94| 73.14| 73.33| 13.02| 3.25 | 79.18| 51.24| 35.46| 41.65|
| Middle | 7.26 | 3.86 | 2.38 | 4.17 | 75.91| 63.92| 66.48| 9.99 | 23.25| 97.04| 56.94| 35.43| 46.96|
| Late   | 35.75| 9.96 | 5     | 85.40| 98.76| 26.85| 17.22| 10.96| 75.61| 54.55| 36.05| 44.38|
| En-De  | 24.02| 0.59 | 26.19| 2.5  | 72.26| 96.16| 43.15| 13.31| 10.76| 92.28| 59.57| 38.12| 49.68|
| Cross  | 52.22| 0.3  | 16.67| 4.17 | 83.94| 81.87| 42.22| 0.14 | 68.02| 91.82| 63.38| 48.84| 54.48|

| Method | C1  | C2  | C3  | C4  | C5  | C6  | C7  | C8  | C9  | C10 | OA   | AA   | κ   |
|--------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|------|-----|
| MSI    | 51.96| 0.15| 0.79 | 35.04| 46.11| 1.45 | 48.22| 64.81| 3.93 | 24.85| 21.92|
| SAR    | 59.78| 27.78| 5.00 | 83.21| 95.98| 39.07| 3.91 | 4.06 | 62.50| 48.47| 38.13| 38.99|
| Early  | 17.88| 3.27 | 22.22| 7.50 | 86.86| 53.16| 76.30| 16.79| 5.89 | 68.57| 44.85| 35.84| 35.56|
| Middle | 3.35 | 23.02| 5.56 | 19.17| 86.86| 93.50| 50.19| 5.93 | 24.87| 91.39| 60.10| 38.00| 50.45|
| Late   | 0.56 | 1.93 | 5.56 | 19.17| 86.86| 93.50| 50.19| 5.93 | 24.87| 91.39| 60.10| 38.00| 50.45|
| En-De  | 47.49| 33.33| 28.33| 1.46 | 42.08| 66.83| 69.04| 89.67| 50.29| 31.14| 39.09|
| Cross  | 93.30| 7.14 | 29.17| 66.83| 69.04| 89.67| 50.29| 31.14| 39.09| 53.12| 33.21| 41.67|
Fig. 8. Visualization of false-color MS and SAR images, the distribution of training and testing samples, and classification maps of different compared methods using FC-Nets on the MS-SAR LCZ data.

Fig. 9. Visualization of false-color MS and SAR images, the distribution of training and testing samples, and classification maps of different compared methods using CNNs on the MS-SAR LCZ data.

D. Result and Analysis on LCZ Data

We evaluate the proposed MDL framework in a more challenging LCZ datasets (MS-SAR), where the main difficulties lie in two parts. On one hand, unlike the conventional LULC, LCZ defines more complex categories within a pixel at a very low spatial resolution, i.e., 100m. In this case, more diverse features and more powerful models are needed. On the other hand, due to completely different imaging mechanism, MS and SAR data are highly heterogeneous, posing a great challenge to the fusion of the two data in networks. Moreover, we select the datasets to investigate the network performance,

visual, spectral, and other cues from highly complex materials lying in the image scene, thereby leading to a accurate reasoning result closer to the ground truth.

- In particular, the building-related types, e.g., Residential, Commercial, can be recognized better by en-de fusion or cross fusion, while some categories in the region covered by the cloud, such as Road, Highway, or Grass, can be identified more accurately in CML-HSI using the compactness-based fusion strategy, due to more effective information transfer from LiDAR data.
e.g., transferability across cities (from Berlin to Hong Kong). As a result, the aforementioned factors can well explain that the classification performance in LCZ data (MSI and SAR) is inferior to that in Houston data (HSI and LiDAR), particularly in the result comparison between LiDAR data and SAR data when considering the CML’s case.

1) Quantitative comparison: As listed in Tables VI and VII, there is a basically consistent trend in performance gain with that on the HS-LiDAR Houston2013 datasets. In general, the results of using the proposed MDL-RS framework are much better than those of only using single modalities (averagely 10% increase in OA, AA, and κ), while the CNN-based methods, as expected, exceed the FC-based ones at an increase of around 10% in terms of all three indices. Despite so, we have to admit that our MDL-RS, to some extent, fails to recognize some materials, such as Open High-rise, Open Low-rise, Scattered Trees, and Bush and Scrub, especially in the CML’s case. This may be due to imbalanced sample distribution and limited feature discrimination for the challenging LCZ categories. Moreover, the compactness-based networks outperform others remarkably at an improvement of over 5% OA, despite relatively low accuracies for certain categories obtained. It should be emphasized, however, that in CML those concatenation-based methods, i.e., early fusion, middle fusion, and late fusion, are incapable of identifying even finding out certain materials in CML-MSI for example. It is much worse in CML-LiDAR, where all materials are recognized as Water. On the contrary, either en-de fusion or cross fusion obtain better classification results, in particular, the latter brings a further improvement of almost 5% OA over the former.

2) Visual comparison: Similarly, visual differences between the classification maps of different networks are shown in Figs. 8 and 9 for FC-Nets’ and CNNs’, respectively. In MML, the cross fusion in our MDL-RS obtain a smoother and more detailed appearance in comparison with other fusion approaches, due to its use of cross learning strategy to eliminate the gap between modalities more effectively. A similar conclusion can be made in the en-de fusion method with a slightly low accuracy compared to the cross fusion. Moreover, the compactness-based methods are more robust against various image degradation, e.g., noise, stripe, etc., than others, as shown in Figs. 8 and 9 where a direct evidence is given. For the CML’s case, all pixels in the scene are assigned with the label of Water using concatenation-based methods, which indicates a weak network’s transferability across different modalities. It should be noted, however, that although the performance of the compactness-based methods is somewhat degraded in the CML’s issue compared to that in the MML’s, the transferability still remains desirable (see both Figs. 8 and 9).

V. Conclusion

In this paper, we propose a general MDL framework that consists of two subnetworks: Ex-Net and Fu-Net, aiming to provide a baseline solution for pixel-level RS image classification tasks using multimodal data. For this purpose, we investigate several different fusion strategies in networks with a focus on three questions: “what”, “where”, and “how” to fuse, as well as two kinds of feature extractors: FC-Nets and CNNs, which can be applicable to pixel-based and spatial-spectral classification, respectively. Apart from the well-studied MML problem, our MDL-RS framework also attempts to drive the research on the issue of CML that widely exists in practice but is less investigated. It should be emphasized, however, that we generalize four well-known fusion modules, e.g., early fusion, middle fusion, late fusion, and en-de fusion into the proposed MDL-RS framework, and additionally propose a novel fusion strategy: cross fusion that not only performs better in MML but also is well applicable to CML. Experimental results conducted on two different multimodal RS datasets demonstrate the effectiveness and superiority of our MDL-RS networks compared to single modalities, and further the compactness-based fusion strategy is superior to the concatenation-based one as well, especially in the CML’s case. In summary,

- In the “what” question, we mainly consider what kinds of modalities are used or fused in our MDL-RS framework. In this paper, we make the quantitative and visual comparison by using two different heterogeneous data, e.g., HS and LiDAR, MS and SAR, for RS image classification, and give a systematic and comprehensive analysis and discussion in the experimental section.
- In the “where” question, we investigate several well-known fusion modules, e.g., early fusion, middle fusion, late fusion, which are corresponding to three different fusion locations in networks, respectively. By quantitative and qualitative assessment, we found that the middle fusion and late fusion tend to yield better classification results, particularly middle fusion. It should be noted that as shown in Fig. 4, the en-de fusion and cross fusion follow the same architecture as middle fusion, that is, their fusion positions are also located in the “middle” of the network.
- In the “how” question, we also discuss two different fusion strategies, i.e., concatenation-based and compactness-based. The former is widely used in MML but usually fails to perform well in CML, while the latter, including en-de fusion and newly-proposed cross fusion show their superiority in blending multimodal features for either MML or CML setting.

However, the RS image classification extremely relies on the quality and amount of samples. Such dependence is stronger for DL-based models. To break the performance bottleneck in MDL, we will introduce weakly-supervised or self-supervised techniques into networks with better-designed fusion modules in the future work.

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