

Implementation of deep neural networks learning on unmanned aerial vehicle based remote-sensing

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ABSTRACT

Due to efficient and adaptable data collecting, unmanned aerial vehicle (UAV) has been a popular topic in computer vision (CV) and remote sensing (RS) in recent years. Inspiring by the recent success of deep learning (DL), several enhanced object identification and tracking methods have been broadly applied to a variety of UAV-related applications, including environmental monitoring, precision agriculture, and traffic management. In this research, we present efficient neural network (ENet), a unique deep neural network architecture designed exclusively for jobs demanding low latency operation. ENet is up to quicker, takes fewer floating-point operations per second (FLOPs), has fewer parameters, and offers accuracy comparable to or superior to that of previous models. We have tested it on the street and cityscapes reports on comparisons with current state-of-the-art approaches and the tradeoffs between a network's processing speed and accuracy. We give measurements of the proposed architecture's performance on embedded devices and offer software enhancements that might make ENet even quicker.

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1. INTRODUCTION

Technological advancements have driven recent interest in home automation devices, augmented reality wearables, and self-driving cars and these have advanced the need for real-time algorithms that can understand visual scenes on low-power mobile devices. These algorithms are called semantic-segmentation algorithms. This need has created a significant gap in the market. These algorithms give every pixel in the picture a class label so that it can be put into the right group. Deep convolutional neural networks (CNNs) [1]–[4] have been able to outperform many standard computer vision methods [5]–[7] in recent times owing to the more access to big datasets and advancements in computational capabilities. When used to the pixel-by-pixel labelling of pictures, CNNs provide results with a poor spatial resolution, even though they are becoming more effective at classification and categorization tasks. Because of this, they are often combined with other algorithms in a process called "cascading" to make the results more accurate. Some examples of these other algorithms are conditional random fields and colour-based segmentation [8], [9].

To spatially identify and finely segment pictures, numerous different designs for neural networks have been developed, such as fully convolutional networks and SegNet [10]–[12]. All these researches are based on an architecture called visual geometry group-16 (VGG16) [13], which is a big model made for categorizing things into more than one class. The networks that these sources suggest have many parameters and take a long time to

figure out. Because of this, they can't be used for many mobile or battery-powered applications that need to process pictures at a processing rate of >10 frames/sec.

In this research, a novel design for neural networks that is aimed at achieving high accuracy while maintaining a high rate of inference speed is proposed. In our research, we decided against implementing any post-processing stages, which, although they are compatible with our methodology and may be used together, would reduce the effectiveness of an end-to-end CNN method. Section 3 describes an encoder-decoder architecture called efficient neural network (ENet); it is both quick and space-efficient. It was made with the help of new guidelines and ideas from the research literature discussed in section 4. The performance of the suggested network was evaluated on street and Cityscapes for real-time driving test-cases while the environment on an interior environment was tested using the scene understanding (SUN) dataset [14]–[16]. The findings are presented in section 5 of the report.

2. RELATED WORK

Understanding the content of pictures and locating the items of interest both need semantic segmentation as a necessary step. This method is of the highest significance in practical contexts like augmented reality and driving assistance systems. In addition, they are required to operate in real time, which highlights the need to give thorough consideration to the design of CNNs. Deep neural networks (NNs) are among the common ways of doing different tasks, such as semantic segmentation. These networks are now one of the most widely used techniques in modern computer vision applications. Because this study provides a novel neural network design, our goal is to compare it to previously published works that carry out the vast majority of inferences in the same manner.

Encoders and decoders, both distinct forms of neural network architecture, are integrated in CNNs to produce the final product. The probabilistic auto-encoders [17], [18] are the basis for the for the design of the encoder-decoder network first described in SegNet-basic [10] and extended in SegNet [11]. Being a standard CNN (just like VGG16 [13]), the encoder is trained to perform input classification while the decoder is a separate network that is used for upsampling the encoder's output [12], [19]–[22]. However, because of their complex topologies and the vast number of parameters, these networks are sluggish during the inference process. The fully connected VGG16 layers, in contrast to fully convolutional networks (FCN) [12], were not incorporated in the latest SegNet iteration; the aim is to reduce the amount of floating-point operations and the networks memory utilization, thereby increasing its compactness. However, they are only capable of functioning in real time.

Other current designs make use of more straightforward classifiers and then, as a post-processing step, cascade these classifiers with a conditional random field (CRF) [9], [23]. These methods need laborious post-processing processes, as shown in [11], and they mostly fail in the identification of classes that occupy a smaller number of pixels in a frame. There is more evidence of these shortcomings in [11]. CNNs can also be added to recurrent neural networks [20] to make them more accurate, but this will slow down the network's speeds. Also, it's important to remember that recurrent neural network (RNN), which is incorporated a post-processing step, is compatible with any other approach, including the described technique in this research.

3. NETWORK ARCHITECTURE

The ENet architecture suggests potential boundary boxes in images using local suggestion techniques. The boundary boxes are then further categorised, processed, and identical ones are eliminated. Finally, the boundary boxes are reassessed in light of the final set of nearby items. This procedure needs to be used in various places and contexts. Areas with a higher score are categorised as obstacles. This method is done a number of times prior to the specified detection threshold is attained. This approach is accurate and extensively used, but it requires a lot of computing power and is difficult to tune and duplicate to the point where it can be used for fully unmanned aerial vehicle (UAV) functions [24]. On the other hand, the semantic segmentation method utilising OpenCV uses a separate neural network to divide an image into sections, evaluate each sector, and determine its boundary boxes. These boundary boxes are categorised based on the results of their evaluations. Using this approach has the advantage that the full image is processed and, although being divided into portions, is still analysed [25].

With the OpenCV, semantic segmentation aims to recognise things as tensor regression expressions. The procedure begins with the algorithm receiving an image as input, where the images' parameters must follow the configuration (nmx3, where 3 stands for the number of colour channels). The $512 \times 512 \times 3$ was utilised in all the tests listed in Table 1 because the initial readings from the trials revealed that the size of the ideal image is 512×512 . A consistently sized grid, abbreviated as (SS), is layered over the image after it has been reduced in size. The steps of detection, categorization, and decision-making are shown in Figure 1 [26].

Table 1. The output sizes are in the input (512 of 512) for E-Net architecture [26]

Name	Type	Output size
Initial		16×256×256
Bottleneck1.0	Downsampling	64×128×128
4x bottleneck1.x		64×128×128
Bottleneck2.0	Downsampling	128×64×64
Bottleneck2.1		128×64×64
Bottleneck2.2	Dilated 2	128×64×64
Bottleneck2.3	Asymmetric 5	128×64×64
Bottleneck2.4	Dilated 4	128×64×64
Bottleneck2.5		128×64×64
Bottleneck2.6	Dilated 8	128×64×64
Bottleneck2.7	Asymmetric 5	128×64×64
Bottleneck2.8	Dilated 16	128×64×64
<i>Repeat section 2, without bottleneck2.0</i>		
Bottleneck4.0	Upsampling	64×128×128
Bottleneck4.1		64×128×128
Bottleneck4.2		64×128×128
Bottleneck5.0	Upsampling	16×256×256
Bottleneck5.1		16×256×256
Fullconv		C×512×512

The system is built to identify, categorise, and make decisions about certain fields and objects. The application applies a variety of approaches depending on the situation, such as biomedical treatment distribution for plants like rice fields and/or avoiding homes, people, and animals. The drone system's semantic segmentation algorithm uses OpenCV to look through a stream of footage only once and make decisions in real time. A third party, such as a person, might monitor the entire system and take action in the most urgent situations [26]. A single block, seen in Figure 1(a), makes up the first stage. We adopt a residual networks (ResNets) model [26] in which extensions branch out from the main branch using convolutional filters and re-join it using element-wise addition. This model is depicted in Figure 1(b). Figure 2 shows the different roads and streets provided as inputs to ENet. The figure also includes the output images segmentation.

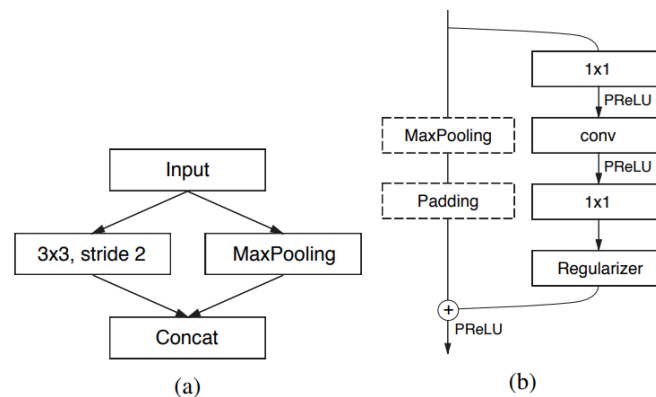


Figure 1. Module structure diagram, (a) ENet initial block and (b) ENet bottleneck module

Filters specifically created for this purpose are used for detection, and ENet architecture is used for clustering and classification to produce real-time decision-making. The hybrid system's usage of semantic segmentation utilising OpenCV and ENet architecture increases the system's robustness, reliability, and intelligence in decision-making while decreasing the number of crucial decisions [26] as show in Figure 2. (ResNet) are popular NN used to perform numerous tasks in computer vision; this is why it was recognized as the ImageNet challenge winner in 2015 [27]–[30]. ResNet was introduced as a game-changer that allowed the successful training of extraordinarily deep neural networks (DNNs) with 150+ layers [31], [32]. However, the problem of vanishing gradients provides that the training of very DNNs is a difficult task before ResNet. The skip connection concept was first presented by ResNet as depicted in the diagram in Figure 3. The graphic on the left shows the stacking of the convolution layers on each other. On the right, the convolution layers were also stacked as previously, but now with the inclusion of the original input in the input of the convolution block. This is termed a skip connection; here, skip connections work for the major reasons show in Figure 4. They prevent the vanishing gradient problem by allowing the flow of the gradient through another shortcut path.

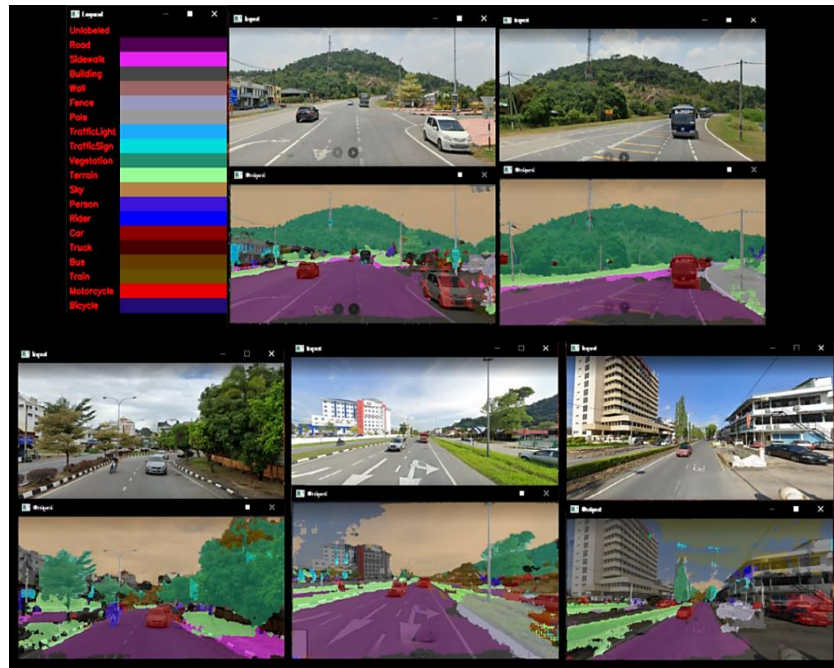


Figure 2. The input images and the output images segmentation in the ENet

They aid in the model's ability to learn an identity function, ensuring that the performance of the higher layer is at least at par with the lower layer. The difficulty of training very deep networks has been reduced by the development of ResNet, which is made up of residual blocks [26]–[30]. When there are differences in the input and output dimensions, this approach cannot perform optimally, as can be seen with pooling and convolutional layers. In this case, the following two approaches can be implemented when the dimensions of $f(x)$ differed from x ; adding more zeros to the skip connection improves the dimensions. Matching the dimension using the projection approach is achieved by padding the input with 1×1 convolutional layer. In this case, the output becomes as [33]. An additional parameter w_1 is introduced here but none is added in the first approach.

$$H(x) = f(x) + w_1 \cdot x \quad (1)$$

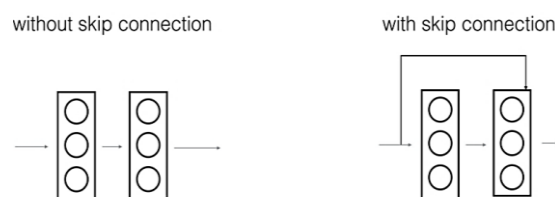


Figure 3. Skip connection

Shallow mesh and deeper mesh structures are shown in Figure 5. A shallow network, also known as a shallow neural network or a shallow model, typically consists of a small number of layers. It usually has a simple structure with only a few hidden layers between the input and output layers. Shallow networks are often used for tasks that have relatively simpler patterns or when the available training data is limited. They are computationally less complex and can be trained relatively faster compared to deeper networks. However, shallow networks may have limited capacity to learn complex patterns and may struggle with tasks that require hierarchical representations or feature abstraction.

Assume we have a shallow and deep network where the function H is used for the conversion of an input ' x ' into an output ' y ' (x); here, it is expected that the deep network should work like the shallow network (at least) without impacting performance negatively as seen with the ordinary NNs that contained no residual blocks [33]. The only way of getting this done is to learn the identity function using another deep network layer in a manner that their output and the inputs are equal, thereby maintaining optimal performance even with"

extra layers as show in Figure 5. Residual blocks are seen to make easy the learning of the identity functions by the layers as seen in (1). The output for the plain networks is (2) [34],

$$H(x) = f(x) \quad (2)$$

so, learning an identity function demands that $f(x)$ must be equivalent to x ; this is grader to achieve but in the case of ResNet, its output is [35],

$$\begin{aligned} H(x) &= f(x) + x \\ f(x) &= 0 \\ H(x) &= x \end{aligned} \quad (3)$$

the only requirement is to make $f(x)=0$ and this is easier, and x will be realized as the output which is equally our input. For the best-case scenario, additional DNN layers can offer better mapping of 'x' to output 'y' than the shallow NN; it will also reduce the error significantly. Hence, the ResNet is expected to perform similarly or better than the ordinary DNNs.

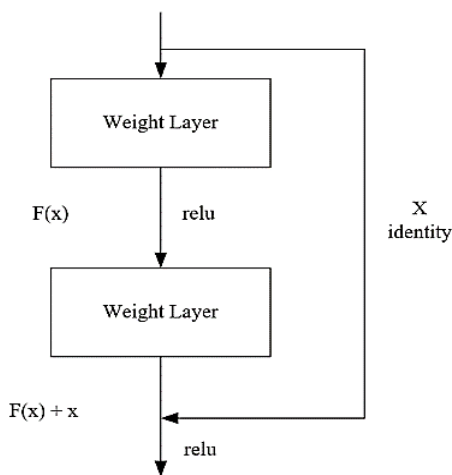


Figure 4. Residual learning: A building block

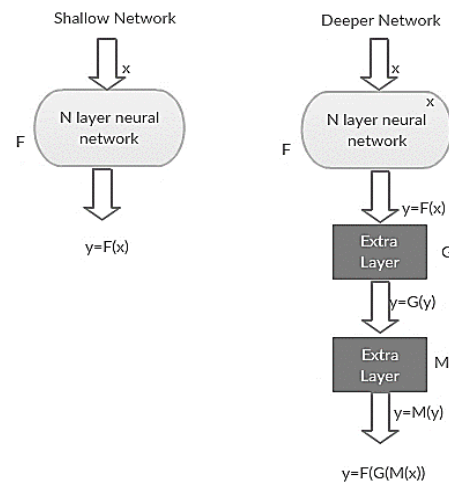


Figure 5. G and M act as identity functions both the network give the same output

4. CONCLUSION

Deep learning is still considered a “black-box” approach for many issues; however, current studies are working to diminish this perception at a rapid pace. Nevertheless, in the field of remote sensing, most applications have benefited through contributions by deep learning-based methods. The aim of this literature survey was to detail the implementation of these approaches in UAV-related image data computation. For this reason, a thorough examination of the field was provided while enlisting outlines of modern strategies and considerations pertaining to their utilization. This survey is intended to serve as a broad study to epitomize the implementation of deep neural networks on UAV-related operations. Within the scope of UAV-based remote-sensing, the majority of authored literature focused on object identification approaches utilizing RGB technology, despite the fact that many applications such as forest related tasks and controlled-agriculture can be more accurately monitored through multispectral or hyperspectral formats of data. It is essential to expand the collection of openly accessible data clusters attained through UAV-imagery for utilization in configuration and evaluation of related systems. As such, this study shared a cluster of UAV-based data obtained in both environmental and agricultural settings. Convolutional neural networks (CNNs) are currently the more highly embraced network architectures in the field; however, various models developed on the footing provided by CNNs i.e., the long short-term memory (LSTM) network and generative adversarial networks (GANs), are rising in prevalence in the image segmentation field and may be promising for upcoming UAV-related image processing applications. Graphical processing units (GPUs) may boost the performance of deep learning algorithms for real time processing operations; hence, it is essential to explore the possibility of onboard processing systems on UAV devices. There are numerous forthcoming technologies, for instance multitask learning, few-shot learning, open-set, attention-based models, that can be used with each order to produce revolutionary UAV-related image processing models. These technologies can also assist in greatly improving the rationalization capability of deep neural networks.

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


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