Abstract
Object Skeletonization is the process of extracting skeletal, line-like representations of shapes. It provides a very useful tool for geometric shape understanding and minimal shape representation. It also has a wide variety of applications, most notably in anatomical research and activity detection. Several mathematical algorithmic approaches have been developed to solve this problem, and some of them have been proven quite robust. However, a lesser amount of attention has been invested into deep learning solutions for it. In this paper, we use a 2-stage variant of the famous U-Net architecture to split the problem space into two sub-problems: shape minimization and corrective skeleton thinning. Our model produces results that are visually much better than the baseline SkelNetOn model. We propose a new metric, M-CCORR, based on normalized correlation coefficients as an alternative to F1 for this challenge as it solves the problem of class imbalance, managing to recognize skeleton similarity without suffering from F1’s over-sensitivity to pixel-shifts.

1 Introduction
Skeletonization is an interesting task because it collapses object shapes into their backbone structure, allowing for constructing a minimal representation of it. Such skeletal representation are useful for many purposes. One simple example of that would be object detection by skeleton matching. Another more involved application is anatomical labelling of different parts of the body such as pulmonary airway trees which requires extracting and identifying different branches of such airways. As such, extracting skeletons can be utilized in shape modelling, compression, and analysis [1]. One thing to note about skeletons is that they contained condensed local as well as global features. That is, they contain information about the main shape along with peripheral details.

In spite of the conceptual differences between segmentation and skeletonization, a few famous segmentation models have been observed to perform well when trained for skeletonization. One of these models is the U-Net architecture used for fast segmentation [2]. U-Net is a fully convolutional neural network that takes its U-shape by virtue of its two main paths: the contraction path, and the expansion path. Passing through the contracting path, the network keeps acquiring features (i.e., information) about what the shape its but loses track of where they came from. To remedy that, the expansive path tries to reconstruct the image again from the condensed features along with the residual connections with their origin layers. Naturally, the reconstructed image will be a reduced version of the original one, which is nicely aligned with the idea of skeletonization.

2 Related Work
The skeletonization problem has various approaches including heuristical algorithms and using deep neural nets. For the first approach, numerous mathematical algorithms are demonstrated in [8]. The problem can also be modelled as a pixel-level binary classification problem known as semantic segmentation. In [1], the SkelNetOn 2019 Challenge three datasets were proposed to serve as a benchmark for shape understanding approaches, one of which is the Pixel SkelNetOn, which poses the challenge in extracting the skeleton pixels from a given binary image. The authors propose a baseline model, which is a vanilla pix2pix model [2]. They apply distance transform on the input images and L1 loss scoring an F1 score of 0.6244. In [3], a feature hourglass network (FHN) is used, using a backbone based on VGGNet [9] and side-output integration following it [4]. They score an F1 score of 0.6477. In [3], a modified U-Net based CNN is used alongside the weighted focal loss to overcome the class imbalance problem. Using an ensemble of 8 models they scored an F1 score of 0.75 on the validation set. The same idea of binary classification was used by [10] in their Holistically-Nested Edge Detection (HED) method. The authors use deep supervision on fully connected neural networks and side-output integration. Inspired by the HED method, authors of [5], propose their SkeletonNet encoder-decoder architecture. Similar to HED, the side layers are fused into final output layers. To improve the HED architecture performance, another type of layers is introduced after the up-sampling stage and their outputs are considered side layers. The loss function used is the sum of the binary cross-entropy and Dice Loss. The best F1 score of SkeletonNet is 0.7877.

3 Dataset
In this work, we focus on the Pixel SkelNetOn dataset containing a total of 1,725 binary images on the PNG format of size 256 × 256 pixels. Objects within each im-
Figure 1: High-level view of the 2-stage U-Net architecture composed of the skeletonizer and the corrector models.

4 Methodology

4.1 Two-stage Problem Split

In our method, we split the problem space into two consecutive problems handled by two U-Nets that were trained accordingly. The first sub-problem is concerned with condensing or minimizing input shapes which typically results in a thick skeleton-like shape. The second sub-problem expects a bad skeleton and aims to correct as well as thin it. Our training pipeline consists of two such U-Nets in series. Note that the two models are not trained together, that is, the first-stage model is trained on the original data, then the second-stage one is trained on the outputs of stage 1 and the original target skeletons. This is was experimentally observed to produce better results than training both models together.

4.2 Modified U-Net Architecture

Both models have the exact same structure and hyper-parameters. A high-level view of our modified U-Net architecture is shown in Figure 1. As briefly explained before, a U-Net consists of a contracting path and an expansive one, separated by a bottleneck region. Each contraction (i.e., down-sampling) block contains two convolutional layers with ReLU activation, ending with a $3 \times 3$ stride-2 max pooling layer. On the other hand, each expansive (i.e., up-sampling) block contains one de-convolutional layer followed by two convolutional layers and a concatenation layer. The last concatenation layer combines the last output.

4.3 Weighted Categorical Cross-entropy Loss

Due to the fact that background pixels heavily outnumber skeleton pixels in target images, mistakes in each of them cannot be weighted equally. This is a classic issue of class imbalance which we address in our loss by giving higher weight to misclassifications on the positive class (i.e., skeleton). This incentivizes the model to be more careful with the skeletal region. On that basis, our loss function is a weighted categorical cross-entropy (CCE) computed as:

$$\mathcal{L}(p_t, p_r) = 1 - w * p_t * p_r$$

where $w$ is the class weights ($w_0 \ll w_1$), $p_t$ is the true class (0 for background, 1 for skeleton), and $p_r$ is the predicted probability.

5 Results

5.1 Experimental Setup

We have experimented with multiple U-Net based architectures using different losses and weights. Although there are differences among the architectures, there are some parameters that are fixed across all experiments. These parameters are shown in Table 1.

| Parameter   | Value   |
|-------------|---------|
| Optimizer   | Adam    |
| Learning Rate | 0.001  |
| $\beta_1$   | 0.9     |
| $\beta_2$   | 0.999   |
| Batch Size  | 32      |
| loss        | Weighted CCE |
| Loss weights| $[1, 25]$ |
| Metrics     | $[F1, M-CCORR]$ |

Table 1: Hyper-parameters across architectural experiments

5.2 New Metric Proposal

Though the $F1$ score is used widely on this dataset as an evaluation metric, one issue that arises with it is that it is very sensitive to small pixel-offset errors. If the skeleton image and the ground truth are partially translated (even by few pixels), the $F1$ score decreases dramatically (check Figure 2 for illustration). This pixel-offset sensitivity poorly evaluates good-looking skeletons though they logically match the ground truth. Hence, we propose the usage of template matching as a new translation-aware metric for this problem. We have developed a variant of the normalized cross-correlation coefficient which we call the Matching Cross-correlation (M-CCORR) as defined in the following equation:

$$M-CCORR(y_t, y_p) = \frac{\max(CCORR(y_t, y_p))}{\log_2(D(y_t, y_p) + 2)}$$

where $y_t$ and $y_p$ are the ground truth and prediction output images respectively and $D$ is a function that return the distance between the bounding box center of the ground truth skeleton and that calculated on the
predicted skeleton. This denominator ensures that the Matching CCORR-based metric we are proposing is not only aware of pixel-offsets but also of the logical resemblance between the target and prediction.

5.3 Experiments

We have experimented with multiple stages of our U-Net based architectures, through varying the number of corrector after the skeletonizer models as shown in Figure 1. The architectures are the following:

- **One-Stage (Skeletonizer):** The entire pipeline consists of a single model that performs the whole skeletonization process.

- **Two-Stage (Skeletonizer + Corrector):** The training pipeline consists of two models: a skeletonizer that produces rough skeletons and a corrector which enhances rough skeletons.

- **Three-Stage (Skeletonizer + 2 Correctors):** The training pipeline consists of three models: a skeletonizer and two correctors in series. This adds an extra enhancement layer on its 2-stage predecessor.

The following Table 2 shows our F1 and M-CCORR scores corresponding to every n-stage experiment:

| Model              | F1 Score | M-CCORR |
|--------------------|----------|---------|
| One-Stage          | 0.4866   | 0.5604  |
| Two-Stage          | 0.5968   | 0.6399  |
| Three-Stage        | 0.5802   | 0.6271  |

Table 2: F1 and M-CCORR scores corresponding to different number of stages of the U-Net like model

The two-stage model outperforms both one-stage and three-stage models in both F1 and M-CCORR scores. It has an F1 score of 0.5968 and an M-CCORR score of 0.6399 on the validation set. A single skeletonizer produces thick skeletons causing many false positives reducing the F1 score, which is fine-tuned by the corrector following it in the two-stage model. Adding more than one corrector (i.e., the three-stage model) does not further improve the results.

In addition to the above setups, we have explored multiple other modifications that did not further improve the F1 and M-CCORR scores. These include (but are not limited to): L1, hinge and focal losses, adding a dilation layer before the output, and applying a distance transform on the input images.

6 Conclusion

In summary, our preliminary results have shown that splitting the problem of skeletonization into two stage does indeed bring significant improvement of accuracy. We have also shown that there is a limit to the split-level beyond which performance will not improve. The literature has several solutions that perform very well in one stage, so incorporating them into a similar 2-stage workflow can boost their accuracy even further. Last but not least, we have demonstrated how sensitivity to translation in the F1 score undermines its representativeness of skeleton quality - proposing normalized correlation coefficients in its stead.

References

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Correlation between vote and self-duty

-0.4 -0.3 -0.2 -0.1 0.0 0.1 0.2 0.3

raise tax
cut tax
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