ive and negative samples ...
tion. The positive samples correspond to predictions from
ult boxes matched with any of ground truth traffic sign,
re 'matched' means that the intersection over union (IoU)
veen the default box and the ground truth target is larger
0.5. If a default box is not matched with any ground truth
et, then the prediction from the default box is regarded as
gative sample.

Ve use the softmax loss as shape classification loss
$_{ape}(\mathbf{s})$ for all positive and negative samples, and use
oth ℓ1 loss [40] as vertex regression loss $L_{vertex}(\Delta\mathbf{p}^i)$
y for positive samples. For negative samples, the vertex
ression loss is not assigned. The overall training loss for
single image is the sum of the shape classification loss
$_{hape}(\mathbf{s})$ and the vertex regression loss $L_{vertex}(\Delta\mathbf{p})$ as
llows,

$$L_{overall}(\mathbf{s},\Delta\mathbf{p}^i) = \frac{1}{K_p+K_n}\lambda_s \sum^{K_p+K_n} L_{shape}(\mathbf{s}) + \frac{1}{K_p}\lambda_v \sum^{K_p}\sum_{i=1}^{4} L_{vertex}(\Delta\mathbf{p}^i), \tag{4}$$

vhere K_p and K_n are the number of positive and negative
amples respectively, and λ_s and λ_v are loss weights for
he shape classification loss and the vertex regression loss
espectively. For notational simplicity, we omit the index of a
default box inside each loss function.

Since multiple default boxes of various aspect ratios are
assigned to each unit of classification and regression layers, it
is usual that the total number of default boxes is significantly
larger than the number of positive samples, and most of the
default boxes become negative samples. To resolve this severe
imbalance between positive and negative samples, we employ
hard negative mining technique [6], [41] to select only few of