Supplementary Materials

For article:

Incorporating label correlations into deep neural networks to classify protein subcellular location patterns in immunohistochemistry images

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Table S1 Mapping subcellular locations of immunofluorescence images in the human protein atlas to five major subcellular locations.

Immunofluorescence subcellular location	Mapped to major subcellular location
Aggresome Cytoplasmic bodies Cytosol Rods & rings	Cytoplasm
Cell junctions Plasma membrane	Plasma membrane
Golgi apparatus	Golgi apparatus
Mitochondria	Mitochondria
Nuclear bodies Nuclear membrane Nuclear speckles Nucleoli Nucleoli fibrillar center Nucleoplasm Nucleus	Nucleus

Table S2 Experimental results of using different beam sizes.

Beam size	**Subset accuracy**	**Accuracy**	**Precision**	**Recall**	**F1-score**
1	0.575	0.665	0.751	0.667	0.694
2	0.580	0.670	0.757	0.675	0.701
3	0.581	0.671	0.757	0.675	0.701

Table S3 Experimental results of screening the dataset.

Iteration number	**Subset accuracy**	**Accuracy**	**Precision**	**Recall**	**F1-score**
M=0 *	0.553	0.652	0.719	0.684	0.686
M=1	0.575	0.673	0.741	0.703	0.707
M=2	0.585	0.676	0.743	0.699	0.707
M=3 *	0.594	0.682	0.748	0.705	0.713
M=4	0.582	0.675	0.742	0.704	0.709

* M=0: CNN without data screening; M=3: deep model used as encoder in laceDNN.

Table S4 Experimental results of whether incorporating label correlations. The results are obtained by five-fold cross validation.

Method†	**Subset accuracy**	**Accuracy**	**Precision**	**Recall**	**F1-score**
CNN	0.554	0.652	0.719	0.684	0.686
CNN^{S}	0.594	0.682	0.749	0.705	0.713
$CNN+LSTM^{WP}$	0.563	0.654	0.744	0.654	0.684
$CNN+LSTM^{P}$	0.581	0.671	0.758	0.676	0.701
Liu et al. (CNN+LSTM)	0.398	0.422	0.445	0.422	0.429
Islam et al. (CNN+LSTM)	0.447	0.504	0.572	0.506	0.527
Wang et al. (CNN+LSTM)	0.559	0.653	0.744	0.652	0.683
laceDNN (CNN^{S}+LSTM)	0.614	0.707	0.798	0.709	0.738

† CNN: CNN trained on the initial dataset. CNN^{S}: CNN fine-tuned with screened dataset. $LSTM^{WP}$: LSTM without using the predicted probabilities. $LSTM^{P}$: LSTM incorporating the label correlations (predicted probabilities). laceCNN: our final proposed method.