Dynamic Pruning of Factor Graphs for Maximum Marginal Prediction – Supplemental Material –

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The supplemental material contains larger and more complete versions plots of the figures in the main manuscript.

Adaptive Sampling for Maximum Marginal Prediction
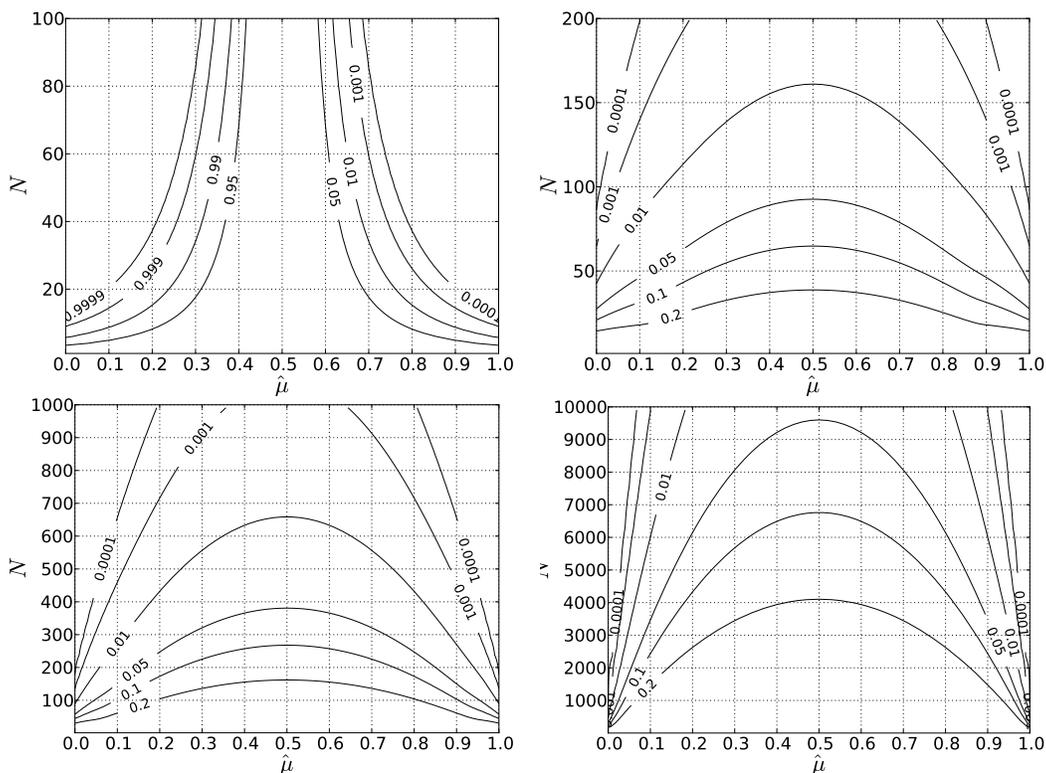
Figure 1: Illustration that maximum marginal decision is easier than marginal estimation if the marginal distribution is far from 0.5. We assume we have observed N i.i.d. samples from a distribution with $p(x = 1) = \mu$. Top left: expected confidence of $\mu \leq 0.5$, i.e. decision $z = 0$. Other plots: confidence that $\mu \in [\mu - \delta, \mu + \delta]$ for $\delta = 0.1$ (top right), $\delta = 0.05$ (bottom left) and $\delta = 0.01$ (bottom right). Note the differently scaled y-axis.

1

Multi-label classification
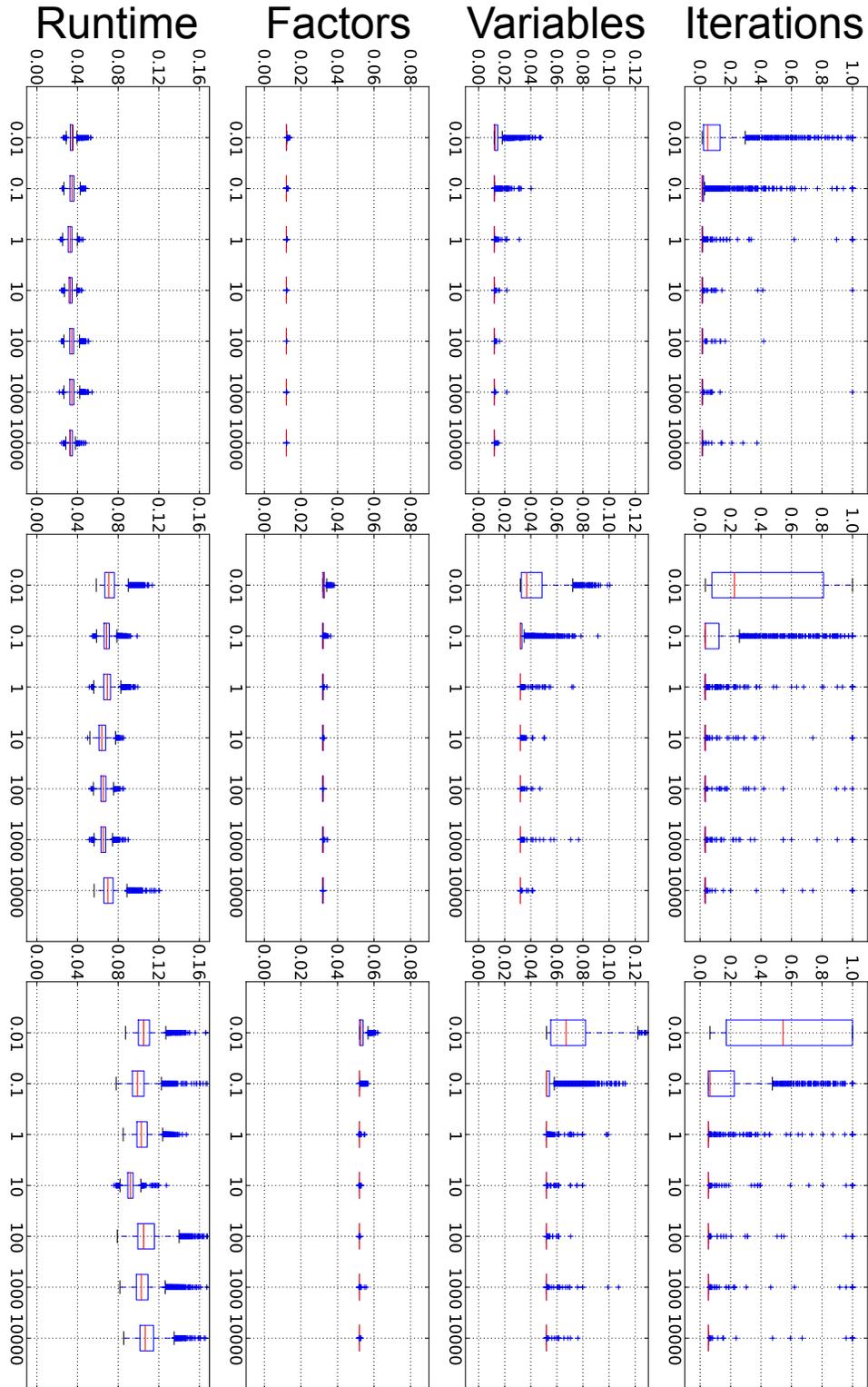
Figure 2: Results of adaptive pruning on RCV1 dataset for $\epsilon = 10^{-2}, 10^{-5}, 10^{-8}$ (left to right). x-axis: regularization parameter C used for training, y-axis: ratio of iterations/variables/factors/runtime used by adaptive sampling relative to 500 iterations Gibbs sampling.

2
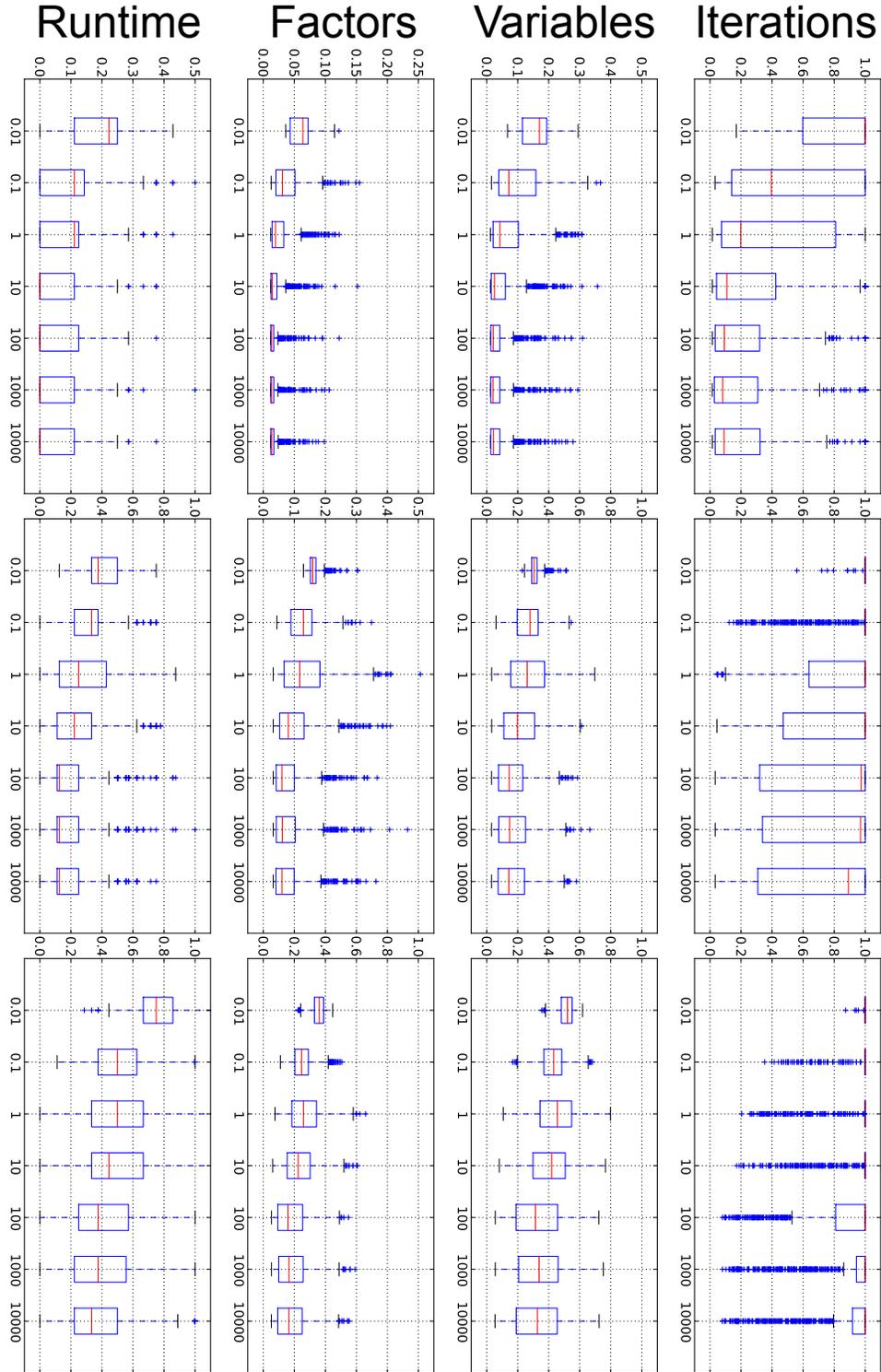
Figure 3: Results of adaptive pruning on YEAST dataset for $\epsilon = 10^{-2}, 10^{-5}, 10^{-8}$ (left to right). x-axis: regularization parameter C used for training, y-axis: ratio of iterations/variables/factors/runtime used by adaptive sampling relative to 500 iterations Gibbs sampling. Beware that the scaling of the y-axis changes between columns.

3
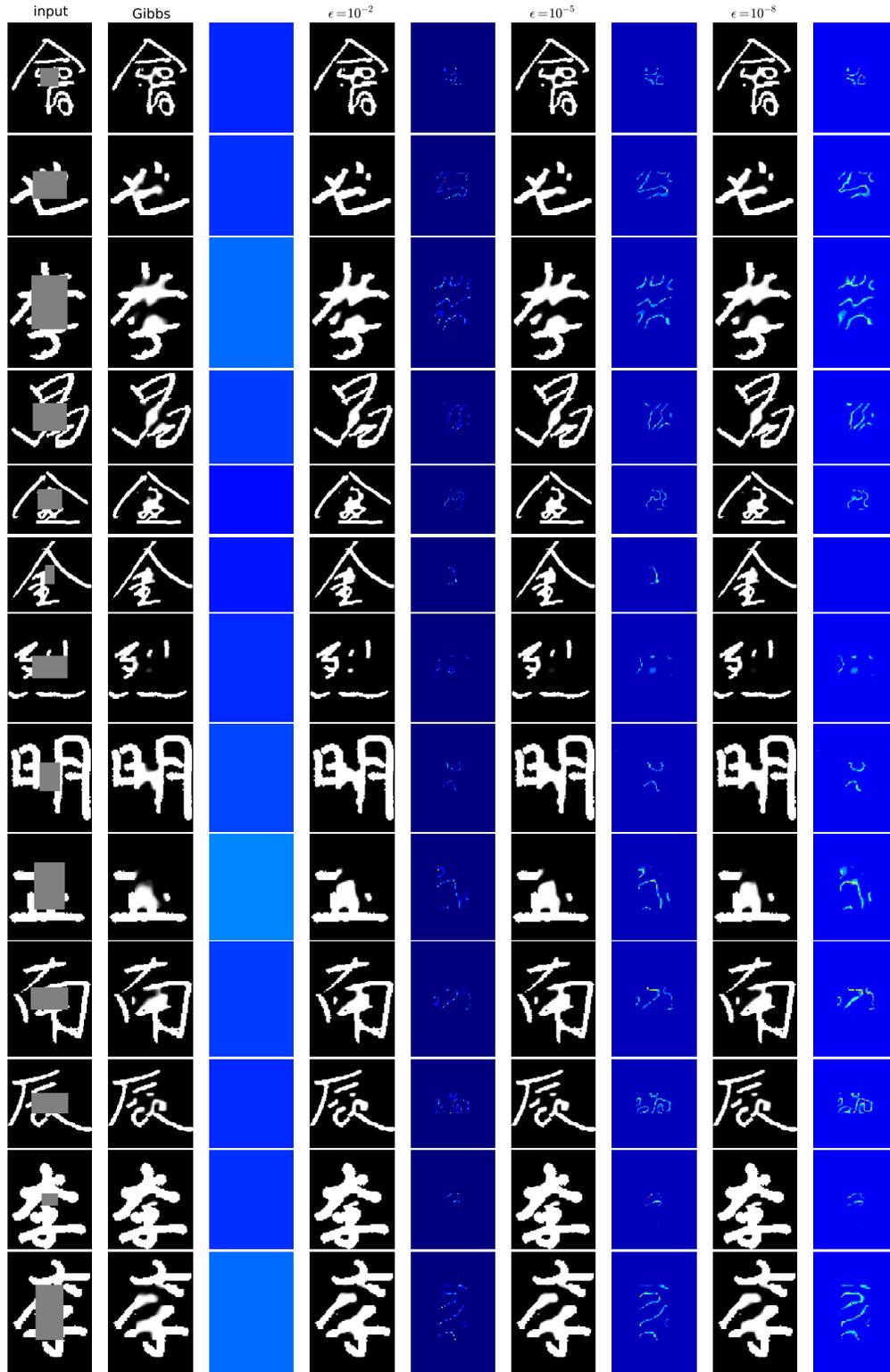
Image inpainting

Figure 4: Example results of binary image inpainting on HECC dataset, images 1–13. Images where the $\epsilon = 10^{-8}$ results is identical to Gibbs are cases where no decision became confident enough within the time limit.

4
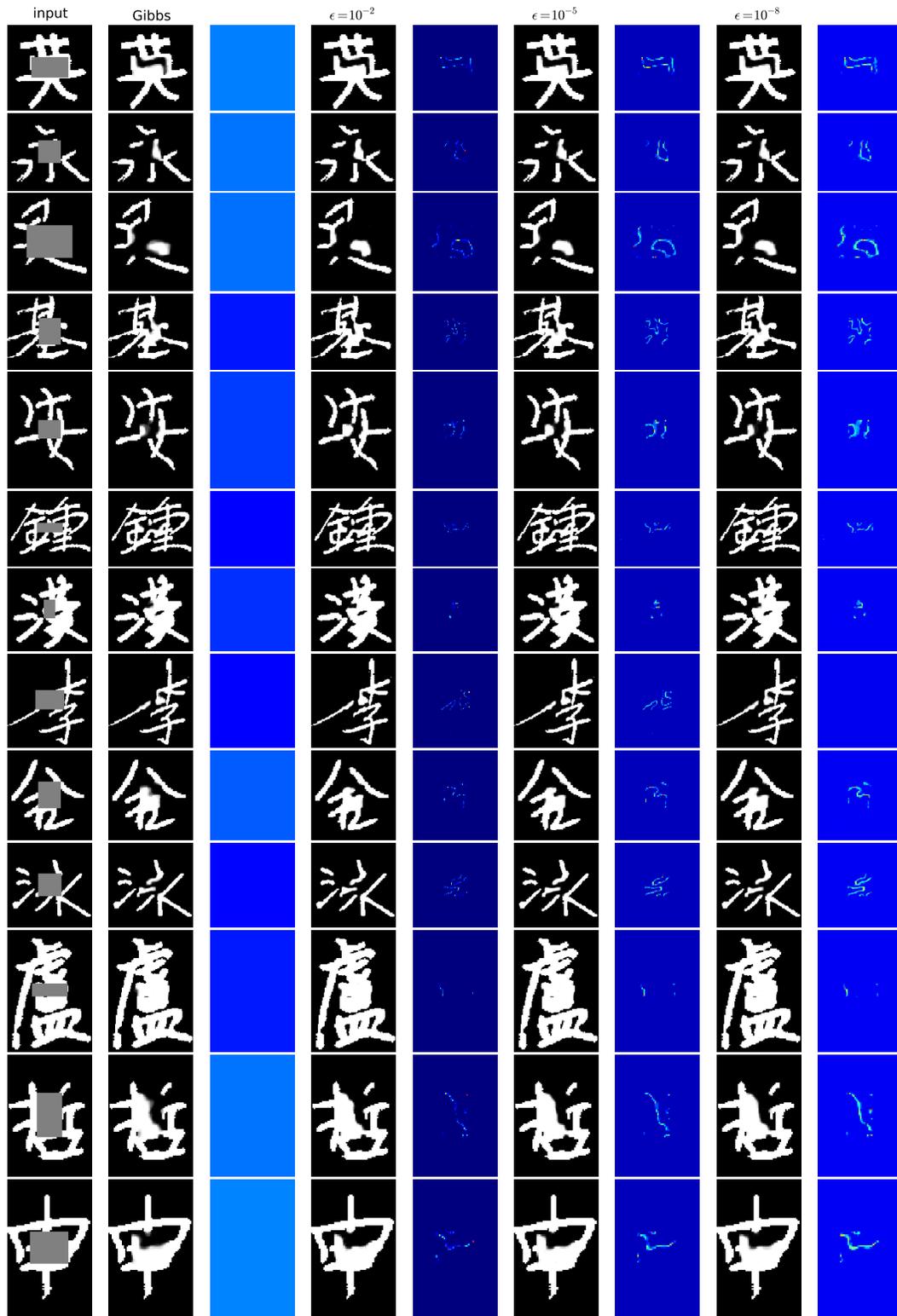
Figure 5: Example results of binary image inpainting on HECC dataset, images 14–26.

5
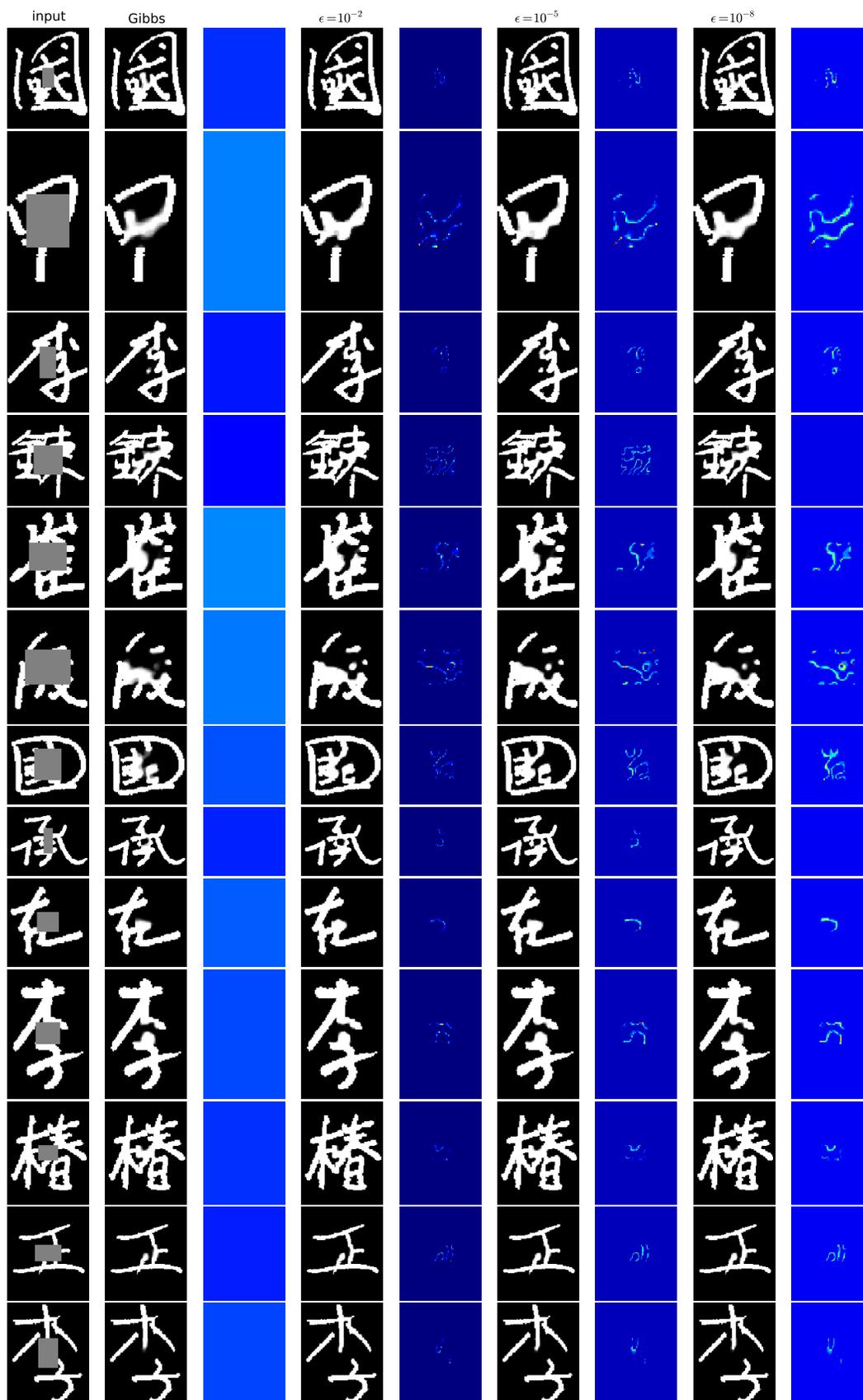
Figure 6: Example results of binary image inpainting on HECC dataset, images 26–39.

6
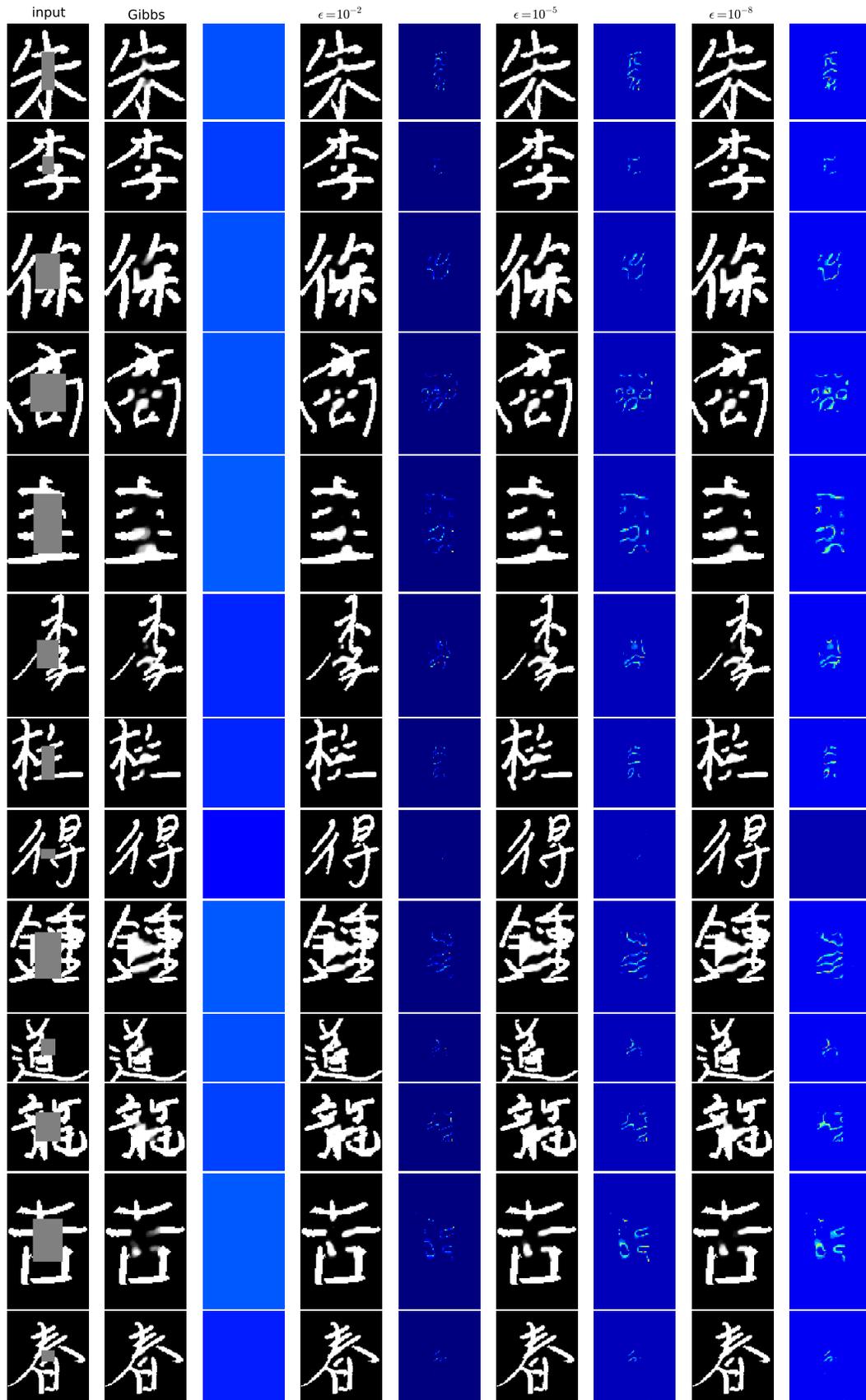
Figure 7: Example results of binary image inpainting on HECC dataset, images 40–52.

7
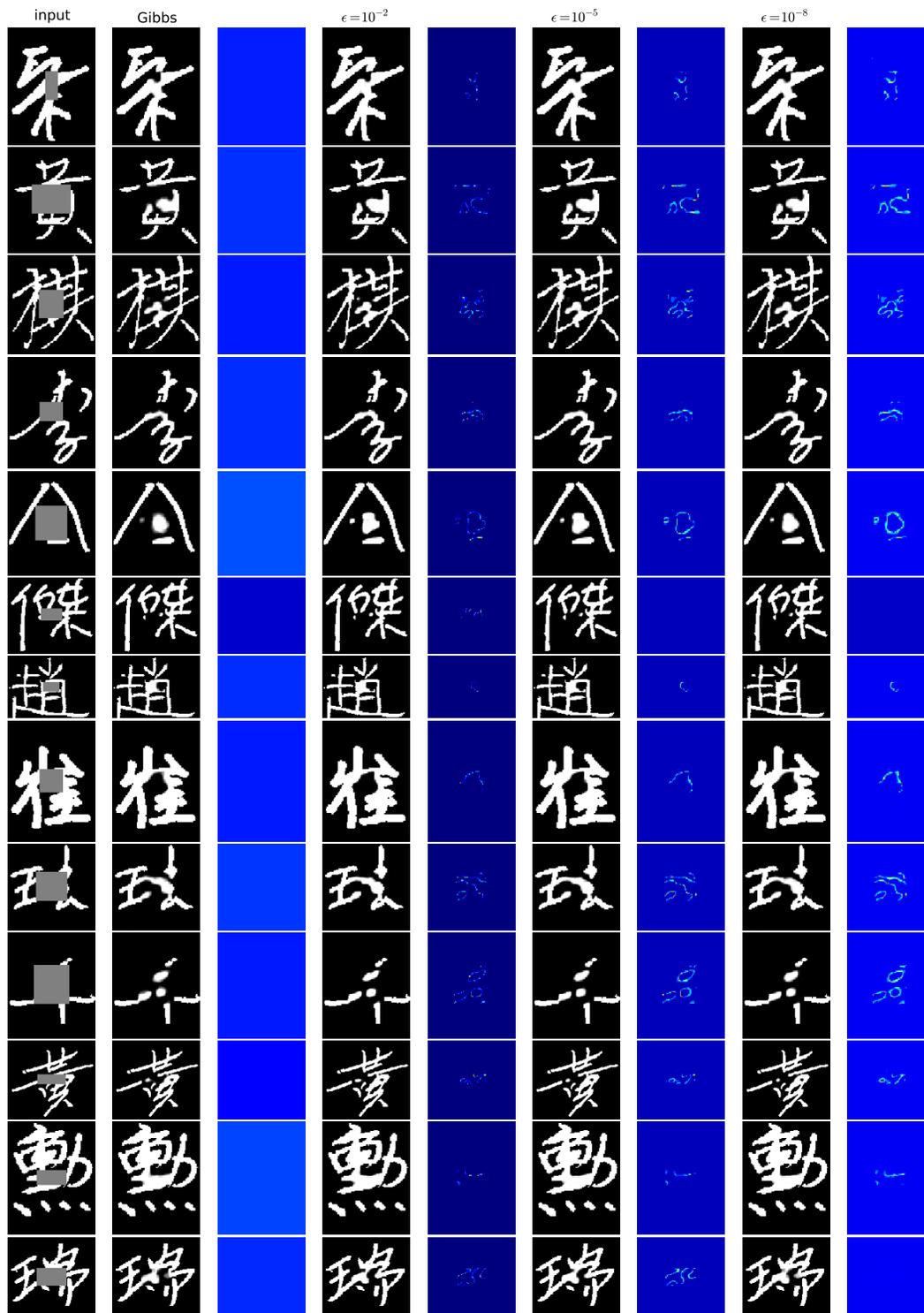
Figure 8: Example results of binary image inpainting on HECC dataset, images 53–65.

8
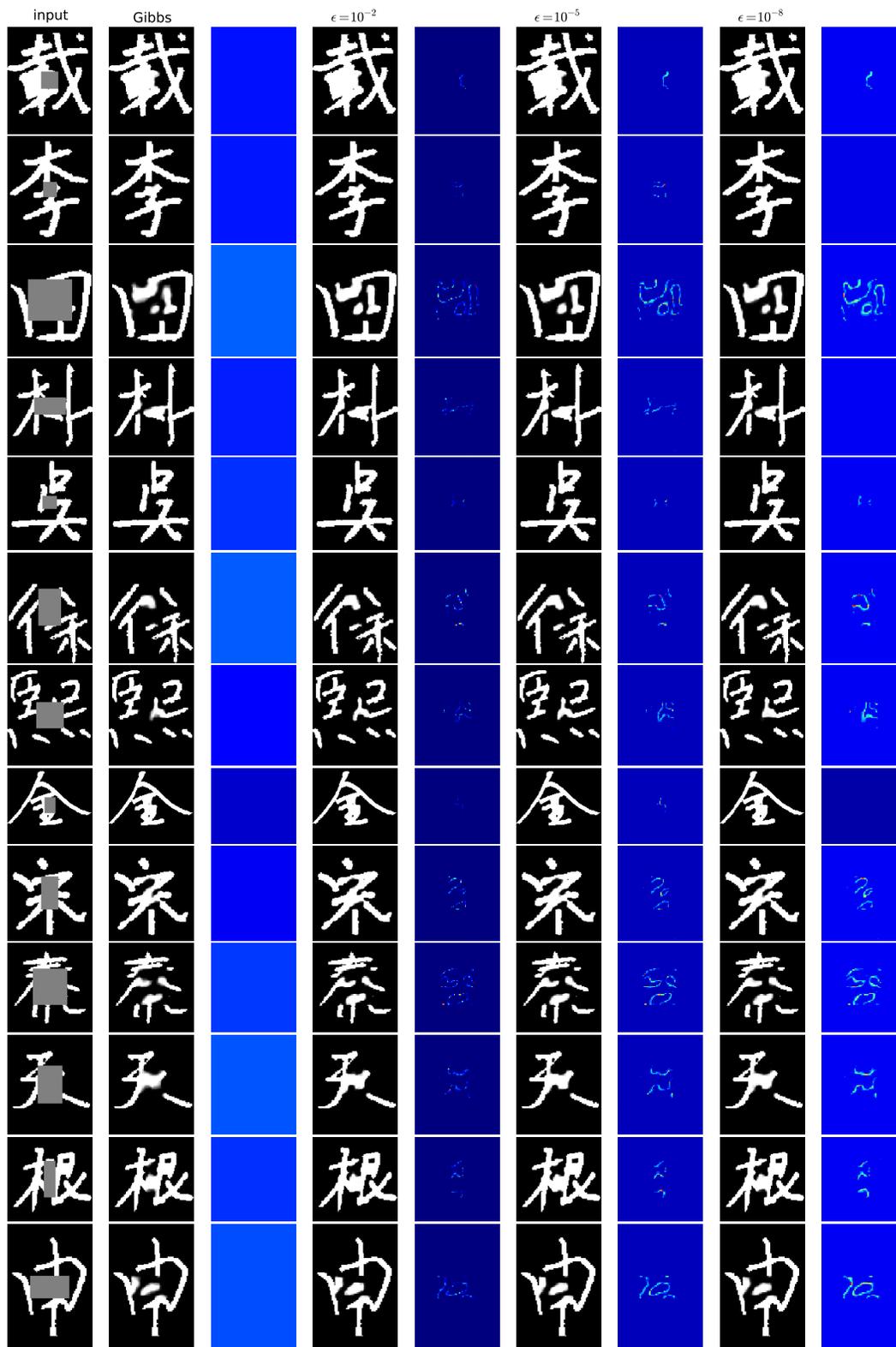
Figure 9: Example results of binary image inpainting on HECC dataset, images 66–78.

9
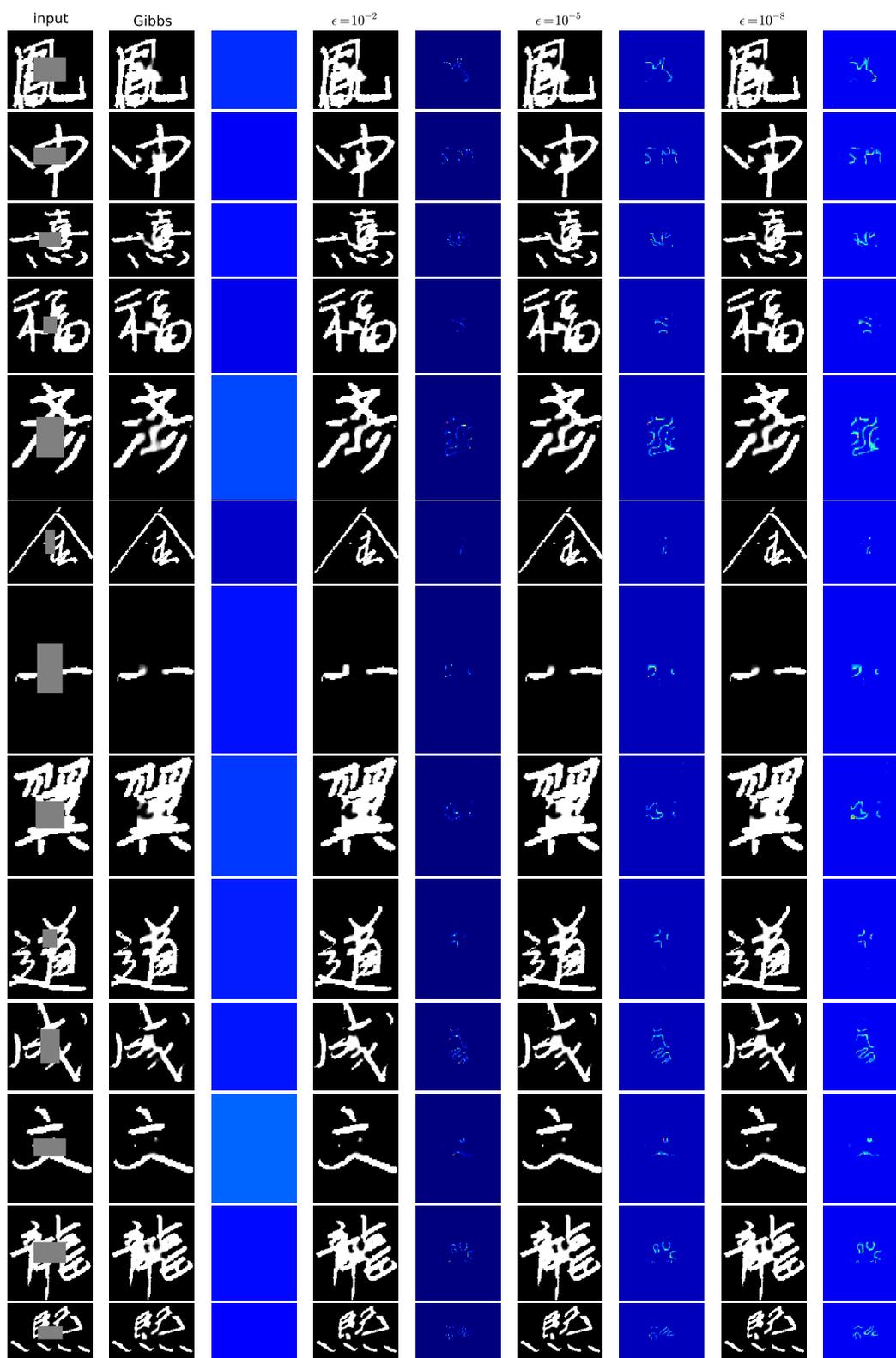
Figure 10: Example results of binary image inpainting on HECC dataset, images 79–91.

10
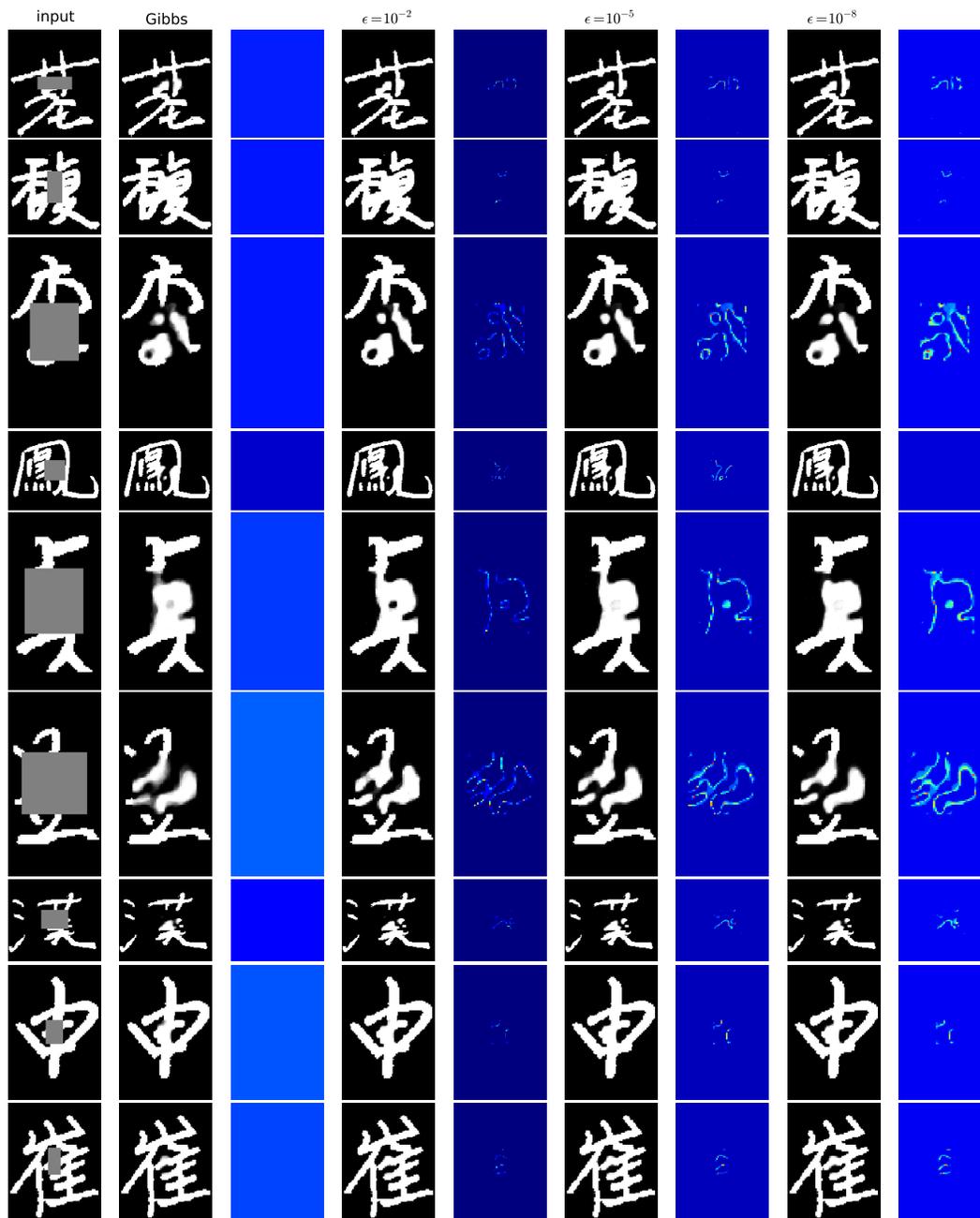
Figure 11: Example results of binary image inpainting on HECC dataset, images 92-100.

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