CLAIMS

1. A method of performing automated cell viability counting, comprising:

capturing an image at a target focus position;

spatially downsampling the captured image to form a downsampled image;

decomposing the downsampled image into a plurality of tiles;

storing the plurality of tiles in a tensor array;

processing the tensor array using a convolutional neural network;

constructing a plurality of pseudo-probability maps based on an output of the convolutional neural network;

thresholding the plurality of pseudo-probability maps to generate binarized location maps and binarized mask maps;

generating a segmented downsampled image by segmenting the downsampled image using the binarized location maps for seeding and the binarized mask maps for delimitating cell areas, wherein the segmented downsampled image indicates/provides a cell viability count; and

displaying a representation of the cell viability count.

2. The method of claim 1, wherein the convolutional neural network is trained with images from multiple focal planes relative to the focus position, preferably ranging from -2 to +2 z-position.

3. The method of claim 1 or claim 2, wherein spatially downsampling the captured image comprises downsampling the captured image by a factor of 2 via pixel decimation, optionally resulting in a 1296 x 972 downsampled image.

4. The method of any one of claims 1-3, wherein decomposing the downsampled image into a plurality of tiles comprises:

reflecting the downsampled image to extend its edges by a plurality of pixels, forming a reflected image; and

decomposing the reflected image into the plurality of tiles with pixel overlap.

5. The method of claim 4, wherein reflecting the downsampled image extends its edges by 4-12 pixels, or 6-10 pixels, or about 8 pixels.

6. The method of claim 4 or claim 5, wherein the reflected image is decomposed into 80-190 tiles, or 90-180 tiles, or 100-170 tiles, or 110-160 tiles, or 120-150 tiles, or about 130 tiles, optionally with size of 128 x 128 pixels with pixel overlap.

7. The method of any one of claims 1-6, wherein the convolutional neural network comprises a U-net convolutional neural network.

8. The method of any one of claims 1-7, wherein the output of the convolutional neural network is stored in a 130 x 4 x 128 x 128 tensor array.

9. The method of any one of claims 1-8, wherein constructing the plurality of pseudo-probability maps comprises converting the output of the convolutional neural network into an 8-bit format tensor and image stitching the 8-bit format tensor.

10. The method of claim 9, wherein converting the output into the 8-bit format tensor comprises multiplying the 130 x 4 x 128 x 128 tensor array by a multiplier, optionally wherein the multiplier is about 255.

11. The method of claim 9 or claim 10, wherein image stitching the 8-bit format tensor comprises constructing 4 full size pseudo-probability maps from the tensor array.

12. The method of claim 11, wherein the output of the convolutional neural network comprises pseudo-probability maps associated with (i) a location of live cells, (ii) a mask of live cells, (iii) a location of dead cells, and (iv) a mask of dead cells.

13. The method of any one of claims 1-12, wherein thresholding comprises applying a threshold value greater than 50% to 90% pseudoprobability, or about 75% pseudoprobability.

14. The method of any one of claims 1-13, wherein the downsampled image is segmented by watershed transform applied on a distance map computed from respective locations of live/dead cells and delimitated by the respective mask of live/dead cells.

15. The method of any one of claims 1-14, further comprising ellipse fitting cells within the segmented downsampled image.

16. The method of claim 15, wherein ellipse fitting comprises identifying one or more objects in an image.

17. The method of claim 16, wherein ellipse fitting comprises measuring object size, constructing a histogram of object size, pixel intensity, and calculating object circularity.

18. A computer system configured to perform automated cell viability counting, comprising one or more processors and one or more hardware storage devices having stored thereon computer-executable instructions that when executed by the one or more processors configure the computer system to perform the method of any one of claims 1-17.

19. A method of performing automated cell viability counting, comprising:

obtaining an image;

defining a set of one or more tiles based on the image;

processing the one or more tiles using a convolutional neural network;

generating a plurality of pseudo-probability maps based on an output of the convolutional neural network, the plurality of pseudo-probability maps comprising at least one or more seed likelihood images; and

generating one or more masks based on the one or more seed likelihood images, the one or more masks defining pixel locations for one or more objects represented in the one or more seed likelihood images, the one or more masks indicating/providing a cell count.

20. The method of claim 19, further comprising performing connected-component analysis on the one or more seed likelihood images to determine the cell count.

21. The method of any one of claims 19-20, wherein the convolutional neural network is trained with a set of training data comprising images from multiple focal planes relative to a focus position, preferably ranging from -2 to +2 z-position.

22. The method of claim 21, wherein the set of training data comprises ground truth output including one or more whole cell binary masks and/or one or more seed masks.

23. The method of any one of claims 19-22, further comprising performing one or more pre-processing operations, wherein the one or more pre-processing operations are performed based on the image to generate a pre-processed image, and wherein the set of one or more tiles is decomposed from the pre-processed image, or the one or more pre-processing operations are performed on the one or more tiles.

24. The method of claim 23, wherein the one or more pre-processing operations comprise a downsampling operation, a background removal operation, and/or a pixel or voxel intensity normalization operation.

25. A method of autofocusing an image, comprising:

optionally, receiving a sample holder at an imaging system;

optionally, based at least in part on the sample holder, automatically determining a z-axis step size for a nominal focus range;

receiving a plurality of images over the nominal focus range;

generating input data based on the plurality of images, the input data being generated via one or more image processing operations;

utilizing the input data as input to a machine learning module configured to provide target focus position output responsive to input generated from images associated with one or more nominal focus ranges;

obtaining a target focus position based on output of the machine learning module; and

configuring the imaging system to capture an image using the target focus position.