

id	Author	paper	DOI	Task	Mode	Application	Summary
28	Sadanandan SK et al. (2016)	Feature augmented deep neural networks for segmentation of cells	<a href="http://doi.org/10.1007/978-3-319-46604-0_17">http://doi.org/10.1007/978-3-319-46604-0_17</a>	S	BF, FL	CL	Improved segmentation using hessian (2nd order derivative) and wavelet filtering of the images with raw inputs to a CNN model.
35	Su H et al. (2015)	Robust Cell Detection and Segmentation in Histopathological Images Using Sparse Reconstruction and Stacked Denoising Autoencoders	<a href="https://doi.org/10.1007/978-3-319-24574-4_46">https://doi.org/10.1007/978-3-319-24574-4_46</a>	S	BF	T	Improved brain tumor and lung cancer diagnosis by segmenting and detecting cells using a stacked denoising autoencoder.
36	Rivenson Y et al. (2017)	Deep learning microscopy: Enhancing resolution, field-of-view and depth-of-field of optical microscopy images using neural networks	<a href="http://doi.org/10.1364/CLEO_AT.2018.AM1J.5">http://doi.org/10.1364/CLEO_AT.2018.AM1J.5</a>	P	BF	T	Enhanced optical microscopy image resolution, depth of field, and field of view without any imaging system modification using a CNN model.
37	Rivenson Y et al. (2018)	Deep Learning Enhanced Mobile-Phone Microscopy	<a href="http://doi.org/10.1021/acsphtonic.8b00146">http://doi.org/10.1021/acsphtonic.8b00146</a>	P	BF	T	Improved mobile phone-based optical image reconstruction by removing distortions and denoising using the CNN model.
38	Weigert M et al. (2017)	Content-Aware Image Restoration: Pushing the Limits of Fluorescence Microscopy	<a href="https://doi.org/10.1101/236463">https://doi.org/10.1101/236463</a>	P	FL	CL	Image restoration of several different cells using a U-Net model.
39	Wang H et al. (2018)	Deep learning achieves super-resolution in fluorescence microscopy	<a href="https://doi.org/10.1101/309641">https://doi.org/10.1101/309641</a>	P	FL	SB	Superresolution reconstruction of low-resolution images into high-resolution images using GAN model.
40	Ouyang W et al. (2018)	Deep learning massively accelerates super-resolution localization microscopy	<a href="http://doi.org/10.1038/nbt.4106">http://doi.org/10.1038/nbt.4106</a>	P	FL	SB	Super-resolution views reconstruction from sparse rapidly acquired localization images and/or widefield images using a CNN model.
41	Nehme E et al. (2018)	Deep-STORM: Super-resolution single-molecule microscopy by deep learning	<a href="http://doi.org/10.1364/OPTICA.5.000458">http://doi.org/10.1364/OPTICA.5.000458</a>	P	FL	SB	Ultrafast and Improved superresolution image reconstruction from fluorescent molecules for localization microscopy using a CNN model.
44	Tellez D et al. (2018)	H and E stain augmentation improves generalization of convolutional networks for histopathological mitosis detection	<a href="http://doi.org/10.1117/12.2293048">http://doi.org/10.1117/12.2293048</a>	C,P	BF	T	Improved classification of HE histological tissue sections by augmenting the image data for a CNN classifier.
47	Ciresan D et al. (2012)	Deep Neural Networks Segment Neuronal Membranes in Electron Microscopy Images	<a href="https://papers.nips.cc/paper/4741-deep-neural-networks-segment-neuronalmembranes-in-electron-microscopy-images">https://papers.nips.cc/paper/4741-deep-neural-networks-segment-neuronalmembranes-in-electron-microscopy-images</a>	S	EM	CL,SB	Automated segmentation of neuronal structures in stacks of EM images to map 3D brain structures and connectivity using a pixel-wise CNN classifier.
48	Ronneberger O et al. (2015)	U-Net: Convolutional Networks for Biomedical Image Segmentation	<a href="https://doi.org/10.1007/978-3-319-24574-4_28">https://doi.org/10.1007/978-3-319-24574-4_28</a>	S	EM	T,CL	Improved segmentation of neuronal structures with a U-Net neural network
49	Çiçek Ö et al. (2016)	3D U-Net: Learning Dense Volumetric Segmentation from Sparse Annotation	<a href="https://doi.org/10.1007/978-3-319-46723-8_49">https://doi.org/10.1007/978-3-319-46723-8_49</a>	S	FL	SB	Automated volumetric segmentation using a CNN model to learn from sparsely annotated volumetric images.
50	Sadanandan K et al. (2017)	Spheroid Segmentation Using Multiscale Deep Adversarial Networks	<a href="https://doi.org/10.1109/iccvw.2017.11">https://doi.org/10.1109/iccvw.2017.11</a>	S	BF	CL	Improved segmentation of different types of spheroids cells in bright-field microscopy images using a new multiscale GAN model.
51	Arbelle A et al. (2017)	Microscopy cell segmentation via adversarial neural networks	<a href="https://doi.org/10.1109/isbi.2018.8363657">https://doi.org/10.1109/isbi.2018.8363657</a>	S	FL	CL	Automated cell segmentation with limited amount of annotated data using Generative adversarial neural network (GAN) model.
54	Haering M et al. (2018)	Automated Segmentation of Epithelial Tissue Using Cycle-Consistent Generative Adversarial Networks	<a href="https://doi.org/10.1101/311373">https://doi.org/10.1101/311373</a>	S	BF	T	Automated segmentation using cycle consistent GAN's trained with weakly prepared image - mask pairs.
58	Hung J et al. (2017)	Applying Faster R-CNN for Object Detection on Malaria Images	<a href="http://doi.ieeecomputersociety.org/10.1109/CVPRW.2017.112">http://doi.ieeecomputersociety.org/10.1109/CVPRW.2017.112</a>	C	BF	CL	Identification and recognition of malaria-infected blood cells stages in brightfield microscopy images using a CNN model.
59	Ciresan C et al. (2013)	Mitosis Detection in Breast Cancer Histology Images with Deep Neural Networks	<a href="https://doi.org/10.1007/978-3-642-40763-5_51">https://doi.org/10.1007/978-3-642-40763-5_51</a>	C	BF	T	Detection of the mitotic tissue in breast histology images using a deep max-pooling pixel-wise CNN classifier.
61	Mao Y et al. (2015)	A hierarchical convolutional neural network for mitosis detection in phase-contrast microscopy images	<a href="http://doi.org/10.1007/978-3-319-46723-8_79">http://doi.org/10.1007/978-3-319-46723-8_79</a>	C	BF	CL	Automated mitosis event detection in time-lapse phase contrast microscopy using Hierarchical CNN model.
62	Durant J et al. (2016)	Very Deep Convolutional Neural Networks for Morphologic Classification of Erythrocytes	<a href="https://doi.org/10.1373/clinchem.2017.276345">https://doi.org/10.1373/clinchem.2017.276345</a>	C	BF	CL	Performance evaluation of morphological erythrocytes classification using a CNN classifier.
63	Fleury D et al. (2018)	Implementation of Regional-CNN and SSD Machine Learning Object Detection Architectures for the Real Time Analysis of Blood Borne Pathogens in Dark Field Microscopy	<a href="https://doi.org/10.20944/preprints201807.0119.v1">https://doi.org/10.20944/preprints201807.0119.v1</a>	C	BF	CL	Comparative investigation of the disparities between Single Shot Detector (SSD), Mobilenet V1 and the Faster R-CNN Inception V2 model.

67	Wei L et al. (2018)	Neural network control of focal position during time-lapse microscopy of cells	<a href="http://doi.org/10.1038/s41598-018-25458-w">http://doi.org/10.1038/s41598-018-25458-w</a>	P	BF	CLLLLLLL	<b>Autofocusing of bright-field and phase-contrast microscopy using a CNN model.</b>
70	Campanella G et al.	Terabyte-scale Deep Multiple Instance Learning for Classification and Localization in Pathology	<a href="https://arxiv.org/abs/1805.06983">https://arxiv.org/abs/1805.06983</a>	C	BF	T	<b>Improved prostate cancer diagnosis by classifying digital tissue slides on a large scale using deep multiple instance learning-based CNN framework.</b>
72	Kensert A et al. (2018)	Transfer learning with deep convolutional neural networks for classifying cellular morphological changes	<a href="https://doi.org/10.1101/345728">https://doi.org/10.1101/345728</a>	C	FL	CL	<b>Prediction of cellular phenotypes mechanisms in response to chemical perturbations using a pre-trained CNN classifier.</b>
73	Pawlowski N et al.	Automating Morphological Profiling with Generic Deep Convolutional Networks	<a href="https://doi.org/10.1101%2F085118">https://doi.org/10.1101%2F085118</a>	C	FL	CL	<b>Automated feature extraction for morphological profiling using a pre-trained CNN classifier.</b>
77	Yu X et al. (2018)	Classify epithelium-stroma in histopathological images based on deep transferable network	<a href="http://doi.org/10.1111/jmi.12705">http://doi.org/10.1111/jmi.12705</a>	C	BF	T	<b>Unsupervised domain adaptation for epithelium-stroma classification using a pre-trained CNN classifier</b>
78	Eulenberg P et al. (2017)	Reconstructing cell cycle and disease progression using deep learning	<a href="https://doi.org/10.1038/s41467-017-00623-3">https://doi.org/10.1038/s41467-017-00623-3</a>	C, P	FL	CL	<b>Automated reconstruction of biological processes from raw images by combining non-linear dimension reduction technique with a CNN model.</b>
79	Doan M et al. (2018)	Label-free assessment of red blood cell storage lesions by deep learning	<a href="https://doi.org/10.1101/256180">https://doi.org/10.1101/256180</a>	C	BF	CL	<b>Automated red blood cells morphologies characterization using a CNN classifier for label-free imaging flow cytometry.</b>
80	Dürr O et al. (2016)	Single-Cell Phenotype Classification Using Deep Convolutional Neural Networks	<a href="https://doi.org/10.1177/1087057116631284">https://doi.org/10.1177/1087057116631284</a>	C	FL	CL	<b>High-content screening-based phenotype classification using CNN classifiers.</b>
81	Pärnamaa T et al. (2017)	Accurate classification of protein subcellular localization from high-throughput microscopy images using deep learning	<a href="http://doi.org/10.1534/g3.116.033654">http://doi.org/10.1534/g3.116.033654</a>	C	FL	SB	<b>Automated detection of the fluorescently-tagged protein cellular compartment in yeast cells using CNN classifier.</b>
82	Kraus Z et al. (2017)	Automated analysis of high-content microscopy data with deep learning	<a href="https://doi.org/10.15252/msb.20177551">https://doi.org/10.15252/msb.20177551</a>	C	FL	SB	<b>Automated classification and localization of protein subcellular structures in yeast cell microscopy images using a localize CNN.</b>
83	Sommer C et al. (2017)	A Deep Learning And Novelty Detection Framework For Rapid Phenotyping In High-Content Screening	<a href="https://doi.org/10.1101/134627">https://doi.org/10.1101/134627</a>	C	FL	CL	<b>Creation of a deep learning pipeline for analyzing high-content screening data.</b>
84	Young H et al. (2017)	Real-time Image Processing for Microscopy-based Label-free Imaging Flow Cytometry in a Microfluidic Chip	<a href="http://doi.org/10.1038/s41598-017-11534-0">http://doi.org/10.1038/s41598-017-11534-0</a>	C	FL	CL	<b>Automated detection of objects in high-throughput microscopy-based label-free IFC in a microfluidic chip using a CNN classifier.</b>
87	Zhang L et al. (2017)	DeepPap: Deep Convolutional Networks for Cervical Cell Classification.	<a href="https://doi.org/10.1109/IBHI.2017.2705583">https://doi.org/10.1109/IBHI.2017.2705583</a>	C	BF	CL	<b>Improved cervical cell classification using a pre-trained CNN classifier.</b>
88	Song Y et al. (2016)	Accurate Cervical Cell Segmentation from Overlapping Clumps in Pap Smear Images	<a href="https://doi.org/10.1109/tmi.2016.2606380">https://doi.org/10.1109/tmi.2016.2606380</a>	S	BF	CL	<b>Automated pre-cancer identification by improved segmentation of cervical cells using a multi-scale CNN for encoding distinct cell appearances.</b>
90	Cruz-Roa A et al. (2017)	High-throughput adaptive sampling for whole-slide histopathology image analysis (HASHI) via convolutional neural networks: Application to invasive breast cancer detection	<a href="https://doi.org/10.1371/journal.pone.0196828">https://doi.org/10.1371/journal.pone.0196828</a>	C	BF	T	<b>Improved invasive breast cancer tissues detection on whole-slide images by combining adaptive sampling method with a CNN classifier.</b>
91	Litjens G et al. (2016)	Deep learning as a tool for increased accuracy and efficiency of histopathological diagnosis	<a href="https://doi.org/10.1038/srep26286">https://doi.org/10.1038/srep26286</a>	C	BF	T	<b>Improved prostate cancer identification and breast cancer metastasis detection in sentinel lymph nodes using CNN-based classifier.</b>
92	Veta M et al. (2018)	Predicting breast tumor proliferation from whole-slide images: the TUPAC16 challenge.	<a href="https://arxiv.org/abs/1807.08284">https://arxiv.org/abs/1807.08284</a>	C, S	BF	T	<b>Presents the broad adoption of CNN models for breast cancer tumor proliferation challenge.</b>
93	Gecer B et al. (2018)	Detection and classification of cancer in whole slide breast histopathology images using deep convolutional networks	<a href="https://doi.org/10.1016/j.patcog.2018.07.022">https://doi.org/10.1016/j.patcog.2018.07.022</a>	C	BF	T	<b>Automated classification of whole slide images (WSI) of breast biopsies into five diagnostic categories using a CNN classifier.</b>
94	Bejnordi E et al. (2017)	Context-aware stacked convolutional neural networks for classification of breast carcinomas in whole-slide histopathology images	<a href="https://doi.org/10.1117/1.jmi.4.4.044504">https://doi.org/10.1117/1.jmi.4.4.044504</a>	C	BF	T	<b>Breast cancer tissue classification by stacking two CNN's for improved feature learning of cellular details and global tissue structures.</b>
95	Bejnordi B et al. (2018)	Using deep convolutional neural networks to identify and classify tumor-associated stroma in diagnostic breast biopsies	<a href="http://doi.org/10.1038/s41379-018-0073-z">http://doi.org/10.1038/s41379-018-0073-z</a>	C	BF	T	<b>Mammographic abnormalities identification in digital images of benign and malignant HE-stained tissue sections using CNN models.</b>
96	Bychkov D et al. (2018)	Deep learning based tissue analysis predicts outcome in colorectal cancer	<a href="https://doi.org/10.1038/s41598-018-21758-3">https://doi.org/10.1038/s41598-018-21758-3</a>	C	BF	T	<b>Colorectal cancer patient outcome prediction from the tumor tissue images using CNN- and RNN-based classifiers.</b>

98	Qaiser T et al. (2018)	HER2 challenge contest: a detailed assessment of automated HER2 scoring algorithms in whole slide images of breast cancer tissues	<a href="https://doi.org/10.1111/his.13333">https://doi.org/10.1111/his.13333</a>	P,C	BF	T	Benchmark for performance comparison of invasive breast carcinoma tissues stained with both HE and IHC for HER2 scoring using CNN models.
99	Sirinukunwattana K et al. (2017)	Gland segmentation in colon histology images: The glas challenge contest	<a href="https://doi.org/10.1016/j.media.2016.08.008">https://doi.org/10.1016/j.media.2016.08.008</a>	S	BF	T	A comprehensive overview of methods applied for segmenting the gland in colon histology images challenge contest.
100	Akram SU et al. (2017)	Cell segmentation proposal network for microscopy image analysis	<a href="http://doi.org/10.1007/978-3-319-46976-8_3">http://doi.org/10.1007/978-3-319-46976-8_3</a>	C, S	FL, BF	CL	Automated detection and segmentation for tracking cells in time-lapse images using regional CNN model.
101	Wang M et al. (2018)	Multicell migration tracking within angiogenic networks by deep learning-based segmentation and augmented Bayesian filtering	<a href="http://doi.org/10.1117/1.JMI.5.2.024005">http://doi.org/10.1117/1.JMI.5.2.024005</a>	S	BF	CL	Automated cell detection by combining CNN with backward Kalman filtering for tracking.
102	Phan H et al. (2017)	An unsupervised long short-term memory neural network for event detection in cell videos	<a href="https://arxiv.org/abs/1709.02081">https://arxiv.org/abs/1709.02081</a>	C	BF	CL	Automated unsupervised cell event detection and classification in cell video sequences using convolutional recurrent neural networks.
104	Kimmel J et al. (2018)	Deep convolutional and recurrent neural networks for cell motility discrimination and prediction	<a href="https://doi.org/10.1101/159202">https://doi.org/10.1101/159202</a>	C	FL, BF	CL	Classification of different motility behaviors of cells in cultures using 3D CNN and RNN along with autoencoders for unsupervised learning.
105	Wang C et al. (2017)	vU-net: accurate cell edge segmentation in time-lapse fluorescence live cell images based on convolutional neural network	<a href="https://doi.org/10.1101/191858">https://doi.org/10.1101/191858</a>	S	FL	CL	Reconstruction of cell edges in time-lapse imagery by integrating a pre-trained encoder and a U-Net model.
106	Su Y-T et al. (2017)	Spatiotemporal Joint Mitosis Detection Using CNN-LSTM Network in Time-Lapse Phase Contrast Microscopy Images	<a href="http://doi.org/10.1109/ACCESS.2017.2745544">http://doi.org/10.1109/ACCESS.2017.2745544</a>	C	BF	CL	Detection of mitotic events in patch sequences by combining CNN and RNN.
107	Tellez D et al. (2018)	Whole-Slide Mitosis Detection in H&E Breast Histology Using PHH3 as a Reference to Train Distilled Stain-Invariant Convolutional Networks	<a href="https://doi.org/10.1109/tmi.2018.2820199">https://doi.org/10.1109/tmi.2018.2820199</a>	C	BF	T	Automated detection of mitotic figures in breast cancer tissue sections using a CNN classifier.
108	Sadanandan K et al. (2017)	Automated Training of Deep Convolutional Neural Networks for Cell Segmentation	<a href="https://doi.org/10.1038/s41598-017-07599-6">https://doi.org/10.1038/s41598-017-07599-6</a>	S	FL	CL	Automated segmentation of cells with training done with fluorescent proteins enabled over the last frame.
121	Ishaq O et al. (2017)	Deep Fish: Deep Learning-Based Classification of Zebrafish Deformation for High-Throughput Screening	<a href="https://doi.org/10.1177/1087057116667894">https://doi.org/10.1177/1087057116667894</a>	C	BF	○	Improved high-throughput classification of whole-body zebrafish deformations in multi-fish microwell plates using a CNN classifier.
126	Mobadersany P et al. (2018)	Predicting cancer outcomes from histology and genomics using convolutional networks	<a href="https://doi.org/10.1101/198010">https://doi.org/10.1101/198010</a>	C	BF	T	Automated patient outcome prediction from digital pathology images by combining traditional survival models with a CNN classifier.
128	Turkki R et al. (2016)	Antibody-supervised deep learning for quantification of tumor-infiltrating immune cells in hematoxylin and eosin stained breast cancer samples	<a href="https://doi.org/10.4103/2153-3539.189703">https://doi.org/10.4103/2153-3539.189703</a>	C	BF	T	Improved quantification of immune cell-rich areas in HE-stained image samples using a CNN classifier.
131	Xie Y et al. (2015)	Deep Voting and Structured Regression for Microscopy Image Analysis	<a href="http://doi.org/10.1016/B978-0-12-810408-8.00009-2">http://doi.org/10.1016/B978-0-12-810408-8.00009-2</a>	C	FL	CL	Automated nucleus centroids localization for voting confidence of overlapping cells using a CNN-based structured regression model.
138	Arteta C et al.	HTX: a tool for the exploration and visualization of high-throughput image assays	<a href="https://doi.org/10.1101/204016">https://doi.org/10.1101/204016</a>	P	BF, FL	T, CL, SB	Interactive visualizing of image-based assays based on visual similarities between the samples for improved exploration of large microscopy datasets.
139	Arvaniti E et al.	Automated Gleason grading of prostate cancer tissue microarrays via deep learning	<a href="https://doi.org/10.1038/s41598-018-30535-1">https://doi.org/10.1038/s41598-018-30535-1</a>	C	BF	T	Automated Gleason grading of prostate cancer tissue microarrays with H&E staining using a patch-based CNN classifier.
140	Auberville M et al.	Deep learning-based detection of motion artifacts in probe-based confocal laser endomicroscopy images	<a href="http://doi.org/10.1007/s11548-018-1836-1">http://doi.org/10.1007/s11548-018-1836-1</a>	C	BF	T	Motion artifacts detection of epithelial tissue from the oral cavity and the vocal folds by fine-tuning a pre-trained CNN classifier.
141	Awan R et al.	Context-Aware Learning Using Transferable Features for Classification of Breast Cancer Histology Images	<a href="https://doi.org/10.1007/978-3-319-93000-8_89">https://doi.org/10.1007/978-3-319-93000-8_89</a>	C	BF	T	Breast cancer tissue classification using the encoded representation of a patch-based CNN within an SVM classifier.
142	Bajic B et al.	Denosing of short exposure transmission electron microscopy images for ultrastructural enhancement	<a href="http://doi.org/10.1109/ISBI.2018.8363721">http://doi.org/10.1109/ISBI.2018.8363721</a>	P	EM	SB	Automated denosing of short-exposure high-resolution TEM images of cilia using a multi-stream CNN model.
143	Baltissen D et al.	Comparison of segmentation methods for tissue microscopy images of glioblastoma cells	<a href="http://doi.org/10.1109/ISBI.2018.8363601">http://doi.org/10.1109/ISBI.2018.8363601</a>	S	FL	CL	Automated glioblastoma cell nuclei segmentation in tissue microscopy images using atrous spatial pyramid pooling (ASPP) for a CNN model.
144	Bekkers EJ et al.	Roto-Translation Covariant Convolutional Networks for Medical Image Analysis	<a href="http://arxiv.org/abs/1804.03393v3">http://arxiv.org/abs/1804.03393v3</a>	S	EM, FL	T, CL	Improved segmentation in histopathology, retinal imaging, and electron microscopy images using a CNN model trained without any augmentations.

145	Bentaieb A et al.	Multi-loss convolutional networks for gland analysis in microscopy	<a href="http://doi.org/10.1109/ISBI.2016.7493349">http://doi.org/10.1109/ISBI.2016.7493349</a>	C, S	BF	T,CL	Colon adenocarcinomas segmentation and classification using a single CNN framework for automated cancer tissue analysis.
146	Boyd N et al.	DeepLoco: Fast 3D Localization Microscopy Using Neural Networks	<a href="https://doi.org/10.1101/267096">https://doi.org/10.1101/267096</a>	C	FL	SB	Automated estimation of fluorophores number and locations in a single frame of super-resolution microscopy using a CNN model.
147	Bozkurt A et al.	A Multiresolution Convolutional Neural Network with Partial Label Training for Annotating Reflectance Confocal Microscopy Images of Skin	<a href="http://arxiv.org/abs/1802.02213v2">http://arxiv.org/abs/1802.02213v2</a>	S	BF	T	Automated annotations of morphological patterns using U-Net architecture for improved skin cancer diagnosis in reflectance confocal microscopy.
148	Bozkurt A et al.	Delineation of Skin Strata in Reflectance Confocal Microscopy Images with Recurrent Convolutional Networks	<a href="http://doi.org/10.1109/CVPRW.2017.108">http://doi.org/10.1109/CVPRW.2017.108</a>	C	BF	T	Skin strata tissue classification in RCM image sequences using a recurrent CNN.
149	Buggenthin F et al.	Prospective identification of hematopoietic lineage choice by deep learning	<a href="http://doi.org/10.1038/nmeth.4182">http://doi.org/10.1038/nmeth.4182</a>	C	BF	CL	Hematopoietic cell lineage choice prediction using a patch-based CNN classifier and a recurrent neural network (RNN) for cellular movement.
150	Buniatyan D et al.	Deep Learning Improves Template Matching by Normalized Cross Correlation	<a href="http://arxiv.org/abs/1705.08593v1">http://arxiv.org/abs/1705.08593v1</a>	C	EM		Improved robustness of template matching by preprocessing images using a siamese CNN trained to maximize the contrast between NCC values.
151	Caicedo C et al.	Weakly supervised learning of single-cell feature embeddings	<a href="https://doi.org/10.1101/293431">https://doi.org/10.1101/293431</a>	P	FL	CL	Automated downstream single cell analysis for replicating the treatment condition using a weakly supervised CNN model.
152	Caicedo JC et al.	Evaluation of Deep Learning Strategies for Nucleus Segmentation in Fluorescence Images	<a href="https://doi.org/10.1101/335216">https://doi.org/10.1101/335216</a>	S	FL	CL	Improved segmentation of cell nuclei in a large manually annotated dataset using a U-Net architecture.
153	Calderon CP et al.	Deep Convolutional Neural Network Analysis of Flow Imaging Microscopy Data to Classify Subvisible Particles in Protein Formulations	<a href="http://doi.org/10.1016/j.xphs.2017.12.008">http://doi.org/10.1016/j.xphs.2017.12.008</a>	C	BF	SB	Process conditions prediction for therapeutic protein formulations by encoding the morphological features of subcellular structures using a CNN.
154	Cao G et al.	A hybrid Cnn-Rf method for electron microscopy images segmentation	<a href="http://doi.org/10.4172/1662-100X.1000114">http://doi.org/10.4172/1662-100X.1000114</a>	S	EM	CL	Automated segmentation of neuronal structures for 3d brain tissue reconstruction by combining hybrid CNN with Random Forest classifier.
155	Carneiro G et al.	Weakly-supervised structured output learning with flexible and latent graphs using high-order loss functions	<a href="http://doi.org/10.1109/ICCV.2015.81">http://doi.org/10.1109/ICCV.2015.81</a>	P	BF, FL	T	Estimation of the number and proportion of classes of microcirculatory supply units (MCSU) using a weakly annotated dataset for a CNN model.
156	Carneiro G et al.	Automatic Quantification of Tumour Hypoxia from Multi-Modal Microscopy Images Using Weakly-Supervised Learning Methods	<a href="http://doi.org/10.1109/TMI.2017.2677479">http://doi.org/10.1109/TMI.2017.2677479</a>	P	BF,FL	T	Improved validation of hypoxia-modified therapies to measure tumor hypoxia by classifying annotations using a weakly-supervised CNN model.
157	Castilla C et al.	Segmentation of actin-stained 3D fluorescent cells with filopodial protrusions using convolutional neural networks	<a href="http://doi.org/10.1109/ISBI.2018.8363605">http://doi.org/10.1109/ISBI.2018.8363605</a>	S	FL	CL	Automated segmentation of actin-stained cells in volumetric confocal microscopy images using a CNN model.
158	Chang Y-H et al.	Human induced pluripotent stem cell region recognition in microscopy images using Convolutional Neural Networks	<a href="http://doi.org/10.1109/EMBC.2017.8037747">http://doi.org/10.1109/EMBC.2017.8037747</a>	C	BF	CL	Automated classification and recognition of induced pluripotent stem (iPS) cell regions behaviour using a CNN for aiding iPS cell culture.
159	Chen L et al.	Deep Learning in Label-free Cell Classification	<a href="https://doi.org/10.1038/srep21471">https://doi.org/10.1038/srep21471</a>	C	BF	CL	Improved phenotypic diagnosis by label-free cell classification in high-throughput quantitative imaging using a CNN classifier.
160	Chen J et al.	Neuron segmentation using deep complete bipartite networks	<a href="http://doi.org/10.1007/978-3-319-66185-8_3">http://doi.org/10.1007/978-3-319-66185-8_3</a>	S	FL	CL	Automatic segmentation of neuronal cells using a instance-wise annotations for a pixel-wise complete bipartite networks (CB-Net) model.
161	Cheng H et al.	Deep-learning-assisted Volume Visualization	<a href="http://doi.org/10.1109/TVCG.2018.2796085">http://doi.org/10.1109/TVCG.2018.2796085</a>	P	EM	SB	Improved high-dimensional feature interactions for volume visualization based on the high-dimensional CNN features spectral methods.
162	Cheng H-C et al.	Volume segmentation using convolutional neural networks with limited training data	<a href="http://doi.org/10.1109/ICIP.2017.8296349">http://doi.org/10.1109/ICIP.2017.8296349</a>	S	EM	SB	Improved segmentation in volumetric microscopy images using factorized convolutions and online feature-level augmentations for a 3D CNN model.
163	Chowdhury A et al.	A computational study on convolutional feature combination strategies for grade classification in colon cancer using fluorescence microscopy data	<a href="http://doi.org/10.1117/12.2255687">http://doi.org/10.1117/12.2255687</a>	C	BF	T	Automated colon cancer grade classification using the encoded representations of a pre-trained CNN within a linear SVM classifier.

164	Chowdhury A et al.	Blood vessel characterization using virtual 3D models and convolutional neural networks in fluorescence microscopy	<a href="http://doi.org/10.1109/ISBI.2017.7950599">http://doi.org/10.1109/ISBI.2017.7950599</a>	C	FL	T	<b>Automated characterization of microvessel morphology in micrographs of brain tissue sections using a CNN classifier for facile quantitative analysis.</b>
165	Chowdhury A et al.	Active deep learning reduces annotation burden in automatic cell segmentation	<a href="https://doi.org/10.1101/211060">https://doi.org/10.1101/211060</a>	S	FL, BF	CL	<b>Automated Cell segmentation using active learning for training a CNN model to reduce annotation burden.</b>
166	Christiansen EM et al.	In Silico Labeling: Predicting Fluorescent Labels in Unlabeled Images	<a href="http://doi.org/10.1016/j.cell.2018.03.040">http://doi.org/10.1016/j.cell.2018.03.040</a>	C	BF	SB	<b>Multiple fluorescent labels prediction from transmitted-light images of unlabeled fixed or live biological cells using a CNN-based in silico labeling (ISL).</b>
167	Coudray N et al.	Classification and Mutation Prediction from Non-Small Cell Lung Cancer Histopathology Images using Deep Learning	<a href="https://doi.org/10.1101/197574">https://doi.org/10.1101/197574</a>	C	BF	T	<b>Classification of the whole-slide lung cell tissue images and prediction of mutated genes in lung adenocarcinoma using CNN-based classifiers.</b>
168	Cruz-Roa A et al.	Accurate and reproducible invasive breast cancer detection in whole-slide images: A Deep Learning approach for quantifying tumor extent	<a href="https://doi.org/10.1038/srep46450">https://doi.org/10.1038/srep46450</a>	C	BF	T	<b>Detection of invasive ductal breast carcinoma tissue images using a CNN classifier for automated tumor extent assessment.</b>
169	Delahunt CB et al.	Automated microscopy and machine learning for expert-level malaria field diagnosis	<a href="http://doi.org/10.1109/GHTC.2015.7344002">http://doi.org/10.1109/GHTC.2015.7344002</a>	C, P	BF	T	<b>Low-cost automated digital microscope for improved detection of malaria infectious diseases using CNN classifier.</b>
170	Delas Peñas K et al.	Analysis of Convolutional Neural Networks and Shape Features for Detection and Identification of Malaria Parasites on Thin Blood Smears	<a href="http://doi.org/10.1007/978-3-319-75420-8_45">http://doi.org/10.1007/978-3-319-75420-8_45</a>	C	BF	T	<b>Improved malaria diagnosis using shape features with a CNN-based classifier.</b>
171	Deng F et al.	Rich feature hierarchies for cell detecting under phase contrast microscopy images	<a href="http://doi.org/10.1109/ICIP.2015.7388195">http://doi.org/10.1109/ICIP.2015.7388195</a>	C	BF	T	<b>Automated detection of cells in phase contrast microscopy images using modified region-based CNN classifier.</b>
172	Diederich B et al.	Using machine-learning to optimize phase contrast in a low-cost cellphone microscope	<a href="http://doi.org/10.1371/journal.pone.0192937">http://doi.org/10.1371/journal.pone.0192937</a>	P	BF	T	<b>Real-time applications for a cellphone microscope to learn a relationship between samples and its optimal light source shapes by a CNN model.</b>
173	Dong B et al.	Deep learning for automatic cell detection in wide-field microscopy zebrafish images	<a href="http://doi.org/10.1109/ISBI.2015.7163986">http://doi.org/10.1109/ISBI.2015.7163986</a>	C	BF	CL	<b>Automated detection of tyrosine hydroxylase-containing cells in larval zebrafish brain wide-field microscopy images using a CNN classifier.</b>
174	Dorkenwald S et al.	Automated synaptic connectivity inference for volume electron microscopy	<a href="http://doi.org/10.1038/nmeth.4206">http://doi.org/10.1038/nmeth.4206</a>	C	EM	CL,SB	<b>Automated identification of different cell types to infer a richly annotated synaptic connectivity by combining CNN and random forest classifier.</b>
175	Drozdal M et al.	Learning normalized inputs for iterative estimation in medical image segmentation	<a href="http://doi.org/10.1016/j.media.2017.11.005">http://doi.org/10.1016/j.media.2017.11.005</a>	S	BF	SB	<b>Automated workflow for segmentation by combing fully CNN with fully convolutional residual networks (FC-ResNets).</b>
176	Fabijańska A et al.	Segmentation of corneal endothelium images using a U-Net-based convolutional neural network	<a href="http://doi.org/10.1016/j.artmed.2018.04.004">http://doi.org/10.1016/j.artmed.2018.04.004</a>	S	BF	O	<b>Improved diagnosis of corneal endothelium by analyzing the size and shape of the endothelial cells in specular microscopy images using a CNN model.</b>
177	Fakhry A et al.	Residual Deconvolutional Networks for Brain Electron Microscopy Image Segmentation	<a href="http://doi.org/10.1109/TMI.2016.2613019">http://doi.org/10.1109/TMI.2016.2613019</a>	S	EM	T	<b>Improved segmentation using a multi-stream residual CNN that capture full-resolution features and contextual information of EM images.</b>
178	Fan M et al.	Global probabilistic models for enhancing segmentation with convolutional networks	<a href="http://doi.org/10.1109/ISBI.2018.8363794">http://doi.org/10.1109/ISBI.2018.8363794</a>	S	FL	CL	<b>Efficient cell segmentations by enforcing prior shape constraints through combined global probabilistic model and a CNN model.</b>
179	Fredericksen MA et al.	Three-dimensional visualization and a deep-learning model reveal complex fungal parasite networks in behaviorally manipulated ants	<a href="http://doi.org/10.1073/pnas.1711673114">http://doi.org/10.1073/pnas.1711673114</a>	S	EM	CL	<b>Identification of a microbial parasite adaptation in the body of its coevolved and manipulated host using CNN models.</b>
180	Fu C et al.	Three Dimensional Fluorescence Microscopy Image Synthesis and Segmentation	<a href="http://arxiv.org/abs/1801.07198v2">http://arxiv.org/abs/1801.07198v2</a>	S	FL	CL	<b>Improved characterization and analysis of 3D microscopy images by nuclei segmentation using spatially constrained cycle-consistent GAN model.</b>
181	Fu C et al.	Nuclei segmentation of fluorescence microscopy images using convolutional neural networks	<a href="http://doi.org/10.1109/ISBI.2017.7950617">http://doi.org/10.1109/ISBI.2017.7950617</a>	S	FL	CL,T	<b>Automated segmentation and counting of the nucleus in volumetric images using a CNN model and a watershed technique.</b>
182	Funke J et al.	Large Scale Image Segmentation with Structured Loss based Deep Learning for Connectome Reconstruction	<a href="http://doi.org/10.1109/TPAMI.2018.2835450">http://doi.org/10.1109/TPAMI.2018.2835450</a>	S	EM	T	<b>Automated prediction of affinities between voxels, followed by iterative region agglomeration using a 3D U-Net architecture.</b>

183	Galal S et al.	Candy Cane: Breast Cancer Pixel-Wise Labeling with Fully Convolutional Densenets	<a href="http://doi.org/10.1007/978-3-319-93000-8_93">http://doi.org/10.1007/978-3-319-93000-8_93</a>	S, C	BF,FL	T,CL	Automated pixel-wise labeling of whole-slide images into normal tissue, benign lesion, in situ carcinoma and invasive carcinoma using a CNN model
184	Godinez WJ et al.	A multi-scale convolutional neural network for phenotyping high-content cellular images	<a href="http://doi.org/10.1093/bioinformatics/btx069">http://doi.org/10.1093/bioinformatics/btx069</a>	C	FL	CL	Automated classification of cells into phenotypes using only the images' pixel intensity values for a multi-scale CNN classifier.
185	Goldsborough P et al.	CytoGAN: Generative Modeling of Cell Images	<a href="https://doi.org/10.1101/227645">https://doi.org/10.1101/227645</a>	C	FL	CL	Morphological profiling of human cultured cells in fluorescence microscopy images using GAN model.
186	Goltsev Y et al.	Deep profiling of mouse splenic architecture with CODEX multiplexed imaging.	<a href="https://doi.org/10.1101/203166">https://doi.org/10.1101/203166</a>	C	FL	CL,T	Single-cell antigen quantification to overlay morphological features with lymphoid tissue characterization at cellular levels using a CNN model.
187	Gopakumar G et al.	Cytopathological image analysis using deep-learning networks in microfluidic microscopy	<a href="http://doi.org/10.1364/JOSA-A.34.000111">http://doi.org/10.1364/JOSA-A.34.000111</a>	C	FL	CL	Cytopathologic analysis by classifying three unlabeled, unstained leukemia cell lines (K562, MOLT, and HL60) using a CNN classifier.
188	Górriz M et al.	Leishmaniasis parasite segmentation and classification using deep learning	<a href="http://doi.org/10.1007/978-3-319-94544-6_6">http://doi.org/10.1007/978-3-319-94544-6_6</a>	S, C	BF	CL,SCL	Automated segmentation of Leishmania parasites and classification into promastigotes, amastigotes, and adhered parasites using U-Net model.
189	Gupta A et al.	Convolutional neural networks for false positive reduction of automatically detected cilia in low magnification TEM images	<a href="http://doi.org/10.1007/978-3-319-59126-1_34">http://doi.org/10.1007/978-3-319-59126-1_34</a>	C	EM	SCL	Improved detection of cilia using a CNN classifier for eliminating false-positives identified by a template matching method.
190	Güven G et al.	Nanoparticle detection from TEM images with deep learning [GEM görüntülerinden derin öğrenme ile nanoparçacık tespiti]	<a href="http://doi.org/10.1109/SIU.2018.8404468">http://doi.org/10.1109/SIU.2018.8404468</a>	C	EM	T,SCL	Automated detection of magnetite particles on TEM images using a CNN classifier.
191	Haberl M et al.	CDDeep3M - Plug-and-Play cloud based deep learning for image segmentation of light electron and X-ray microscopy	<a href="https://doi.org/10.1101/353425">https://doi.org/10.1101/353425</a>	S	BF,FL,EM		A pre-configured publicly available cloud-based framework on Amazon Web Services for image segmentation using CNN model.
192	Haft-Javaherian M et al.	Deep convolutional neural networks for segmenting 3D in vivo multiphoton images of vasculature in Alzheimer disease mouse models	<a href="http://arxiv.org/abs/1801.00880v2">http://arxiv.org/abs/1801.00880v2</a>	S	FL	T,CL	Automated analysis of volumetric in vivo vessels image segmentation using a CNN model.
193	Hagita K et al.	Super-resolution for asymmetric resolution of FIB-SEM 3D imaging using AI with deep learning	<a href="http://doi.org/10.1038/s41598-018-24330-1">http://doi.org/10.1038/s41598-018-24330-1</a>	P	EM	CL	Super-resolution reconstruction of asymmetric 3D images to restore the depth resolution to achieve symmetric resolution using a CNN model.
194	Hay EA et al.	Performance of convolutional neural networks for identification of bacteria in 3D microscopy datasets	<a href="https://doi.org/10.1101/273318">https://doi.org/10.1101/273318</a>	C	FL	CL	Classification of bacteria and non-bacterial objects in larval zebrafish intestines light sheet fluorescence images using a 3D CNN classifier.
195	Heinrich L et al.	Deep learning for isotropic super-resolution from non-isotropic 3d electron microscopy	<a href="http://doi.org/10.1007/978-3-319-66185-8_16">http://doi.org/10.1007/978-3-319-66185-8_16</a>	P	EM	T,SCL	Improved superresolution of 3D electron microscopy images using a CNN model.
196	Hernández CX et al.	Using Deep Learning for Segmentation and Counting within Microscopy Data	<a href="http://arxiv.org/abs/1802.10548v1">http://arxiv.org/abs/1802.10548v1</a>	S	BF	CL	Improved identification of possible failure cases by incorporating uncertainty of a CNN classifier for U2OS cells.
197	Hershko* E et al.	Multicolor localization microscopy by deep learning	<a href="http://arxiv.org/abs/1807.01637v1">http://arxiv.org/abs/1807.01637v1</a>	C, P	FL	CL	Automated designing of phase-modulating elements for improved color differentiation between species using CNN models.
198	Ho DJ et al.	Nuclei detection and segmentation of fluorescence microscopy images using three dimensional convolutional neural networks	<a href="http://doi.org/10.1109/ISBI.2018.8363606">http://doi.org/10.1109/ISBI.2018.8363606</a>	S, C	FL	CL	Simultaneous detection and segmentation of cell nuclei in fluorescence microscopy images using a 3D CNN model.
199	Holmström O et al.	Point-of-care mobile digital microscopy and deep learning for the detection of soil-transmitted helminths and Schistosoma haematobium	<a href="http://doi.org/10.1080/16549716.2017.1337325">http://doi.org/10.1080/16549716.2017.1337325</a>	C	BF	CL	Automated detection and classification of helminths in the mobile-phone microscopy images using CNN classifier.
200	Hou L et al.	Sparse Autoencoder for Unsupervised Nucleus Detection and Representation in Histopathology Images	<a href="https://arxiv.org/abs/1704.00406v2">https://arxiv.org/abs/1704.00406v2</a>	C, S	BF	T	Unsupervised simultaneous nucleus detection and segmentation in histopathology tissue images using a sparse convolutional autoencoder.
201	Hu C et al.	Cerebral vessels segmentation for light-sheet microscopy image using convolutional neural networks	<a href="http://doi.org/10.1117/12.2254714">http://doi.org/10.1117/12.2254714</a>	S	FL	O	Automatic and robust segmentation of cerebral micro-vessels structures in mouse cerebrovascular light-sheet microscopy images using a CNN model.

202	Huang GB et al.	Deep and Wide Multiscale Recursive Networks for Robust Image Labeling	<a href="http://arxiv.org/abs/1310.0354v3">http://arxiv.org/abs/1310.0354v3</a>	C, P	EM	T,SCL	Improved image labeling performance for connectomic reconstruction of neural circuitry from 3d EM data using a multiscale recursive CNN model.
203	Huttunen MJ et al.	Automated classification of multiphoton microscopy images of ovarian tissue using deep learning	<a href="http://doi.org/10.1117/1.JBO.23.6.066002">http://doi.org/10.1117/1.JBO.23.6.066002</a>	C	FL	T	Robust classification of unstained, reproductive tissues in multiphoton microscopy images using CNN classifiers.
204	Ishikawa Y et al.	Brain tumor classification of microscopy images using deep residual learning	<a href="http://doi.org/10.1117/12.2242711">http://doi.org/10.1117/12.2242711</a>	C	BF	CL	Improved segmentation of cell regions from astrocytes and classification of brain tumors using CNN models.
205	Işıl Ç et al.	Resolution enhancement of wide-field interferometric microscopy by coupled deep autoencoders	<a href="http://doi.org/10.1364/AO.57.002545">http://doi.org/10.1364/AO.57.002545</a>	P	BF	SCL	Improved resolution of L-shaped nanostructures images using a coupled autoencoders.
206	Ito E et al.	Virus Particle Detection by Convolutional Neural Network in Transmission Electron Microscopy Images	<a href="http://doi.org/10.1007/s12560-018-9335-7">http://doi.org/10.1007/s12560-018-9335-7</a>	C	EM	SCL	Automated localization of virus particles in TEM images using the probability maps generated by a CNN model.
207	Januszewski M et al.	High-precision automated reconstruction of neurons with flood-filling networks	<a href="http://doi.org/10.1038/s41592-018-0049-4">http://doi.org/10.1038/s41592-018-0049-4</a>	P, S	EM	SCL	Automated tracing of neurons in a dataset obtained by serial block-face electron microscopy of a zebra finch brain using flood-filling CNN model.
208	Jiang B et al.	Convolutional neural networks in automatic recognition of trans-differentiated neural progenitor cells under bright-field microscopy	<a href="http://doi.org/10.1109/IMCC C.2015.33">http://doi.org/10.1109/IMCC C.2015.33</a>	C	BF	CL	Automated pre-processing and classification of neural progenitor cells and non-neural progenitor cells using a novel CNN-based recognition system.
209	Jiang S et al.	Transform- and multi-domain deep learning for single-frame rapid autofocusing in whole slide imaging	<a href="http://doi.org/10.1364/BOE.9.001601">http://doi.org/10.1364/BOE.9.001601</a>	P	BF	T	Focal position prediction using a CNN for improved autofocusing performance under incoherent Kohler illumination, partially coherent illumination.
210	Jimenez-Carretero D et al.	Tox_(R)CNN: Deep Learning-Based Nuclei Profiling tool For Drug Toxicity Screening	<a href="https://doi.org/10.1101/334557">https://doi.org/10.1101/334557</a>	C	FL	CL	Toxicity prediction from images of pre-treated DAPI-stained cells using a CNN classifier.
211	Jo Y et al.	Holographic deep learning for rapid optical screening of anthrax spores	<a href="http://doi.org/10.1126/sciad.v.1700606">http://doi.org/10.1126/sciad.v.1700606</a>	C	BF	CL	Diagnosis of Listeria monocytogenes by classifying living cells using a CNN classifier for the label-free screening in holographic microscopy images
212	Judd N et al.	A pilot study for distinguishing chromophobe renal cell carcinoma and oncocytoma using second harmonic generation imaging and convolutional neural network analysis of collagen fibrillar structure	<a href="http://doi.org/10.1117/12.2288088">http://doi.org/10.1117/12.2288088</a>	C	BF	T	Classification of kidney tumor tissue images acquired with collagen matrix using a CNN classifier to distinguish collagen structure-based entities.
213	Kandaswamy C et al.	High-Content Analysis of Breast Cancer Using Single-Cell Deep Transfer Learning	<a href="https://doi.org/10.1177/1087057115623451">https://doi.org/10.1177/1087057115623451</a>	C	FL	CL	Classification of compounds in the chemical mechanisms of action for identifying cell phenotype affecting substances using a CNN classifier.
214	Kannan S et al.	Segmentation of Glomeruli Within Trichrome Images Using Deep Learning	<a href="https://doi.org/10.1101/345579">https://doi.org/10.1101/345579</a>	C, S	BF	T	Automated detection and segmentation of the glomeruli within digitized kidney biopsy images using a CNN.
215	Kassim YM et al.	Microvasculature segmentation of arterioles using deep CNN	<a href="http://doi.org/10.1109/ICIP.2017.8296347">http://doi.org/10.1109/ICIP.2017.8296347</a>	S	FL	T	Robust segmentations of microvasculature tissues from epifluorescence microscopy imagery of mice dura mater using a CNN framework.
216	Kaur P et al.	Hybrid deep learning for Reflectance Confocal Microscopy skin images	<a href="http://doi.org/10.1109/ICPR.2016.7899844">http://doi.org/10.1109/ICPR.2016.7899844</a>	C	FL	T	Identifying human skin disorders in confocal microscopy images of tissues using texon-based feature vectors as input for a CNN.
217	Khan A et al.	Deep convolutional neural networks for human embryonic cell counting	<a href="http://doi.org/10.1007/978-3-319-46604-0_25">http://doi.org/10.1007/978-3-319-46604-0_25</a>	C	BF	CL	Automated cell counting in time-lapse microscopy images of developing human embryos using a CNN classifier.
218	Khobragade N et al.	Multi-class segmentation of neuronal electron microscopy images using deep learning	<a href="http://doi.org/10.1117/12.2293940">http://doi.org/10.1117/12.2293940</a>	S	EM	CL	Multi-class segmentation of Drosophila third instar larva ventral nerve cord images using a pixel-wise Bayesian SegNet classifier.
219	Khoshdeli M et al.	Feature-Based Representation Improves Color Decomposition and Nuclear Detection Using a Convolutional Neural Network	<a href="http://doi.org/10.1109/TBME.2017.2711529">http://doi.org/10.1109/TBME.2017.2711529</a>	C	FL, BF	CL	Improved color decomposition (CD) and subsequent nuclear detection in multiple imaging modalities using a CNN classifier.
220	Khosravi P et al.	Deep Convolutional Neural Networks Enable Discrimination of Heterogeneous Digital Pathology Images	<a href="https://doi.org/10.1101/197517">https://doi.org/10.1101/197517</a>	C	FL, BF	T	Classification of different histopathology images across different cancer subtypes by fine-tuning pre-trained CNN's.
221	Klibisz A et al.	Fast, simple calcium imaging segmentation with fully convolutional networks	<a href="http://doi.org/10.1007/978-3-319-67558-9_33">http://doi.org/10.1007/978-3-319-67558-9_33</a>	S	FL	CL	Examine neuron activity as a series of images by segmenting fluorescence microscopy time-lapse images using a U-Net architecture.

222	Kose K et al.	A multiresolution deep learning framework for automated annotation of reflectance confocal microscopy images	<a href="http://doi.org/10.1364/MICROSCOPY.2018.MTh2A.1">http://doi.org/10.1364/MICROSCOPY.2018.MTh2A.1</a>	P	FL	CL	Automated annotation of morphological patterns to aid skin cancer diagnosis using a multiresolution nested convolutional autoencoder.
223	Kraus Z et al.	Classifying and segmenting microscopy images with deep multiple instance learning	<a href="http://doi.org/10.1093/bioinformatics/btw252">http://doi.org/10.1093/bioinformatics/btw252</a>	C, S	FL	CL	Classification and segmentation of mammalian and yeast cells using only microscopy image annotations for multiple instance learning of CNN.
224	Kwak JT et al.	Nuclear Architecture Analysis of Prostate Cancer via Convolutional Neural Networks	<a href="http://doi.org/10.1109/ACCESS.2017.2747838">http://doi.org/10.1109/ACCESS.2017.2747838</a>	C	BF	T	Improved prostate cancer diagnosis by identifying epithelial nuclear seeds in prostate tissue specimen samples using a CNN classifier.
225	Kwok S et al.	Multiclass Classification of Breast Cancer in Whole-Slide Images	<a href="http://doi.org/10.1007/978-3-319-93000-8_106">http://doi.org/10.1007/978-3-319-93000-8_106</a>	C	BF	T	Improved breast cancer tissue diagnosis by classifying HE stained WSI images through a patch-based CNN classifier.
226	Laine RF et al.	Structured illumination microscopy combined with machine learning enables the high throughput analysis and classification of virus structure	<a href="https://doi.org/10.1101/266551">https://doi.org/10.1101/266551</a>	C	BF	CL	Fast quality assessment of oncolytic virotherapy and vaccine development for high throughput viral production using a pre-trained CNN classifier.
227	Lee G-G et al.	Stem cell detection based on Convolutional Neural Network via third harmonic generation microscopy images	<a href="http://doi.org/10.1109/ICOT.2017.8336085">http://doi.org/10.1109/ICOT.2017.8336085</a>	C	BF	CL,T	Improved tissue diagnosis by classifying basal cells and stem cells using a CNN classifier to detect stem cells in the stratum basale.
228	Leena Silvester M et al.	Enhanced CNN based electron microscopy image segmentation	<a href="http://doi.org/10.2478/cait-2012-0014">http://doi.org/10.2478/cait-2012-0014</a>	S	EM	T	Improved segmentation of ventral nerve cord in EM images using perceptual grouping via a graph cut and its combinations with CNN.
229	Li H et al.	A Hierarchical Convolutional Neural Network for vesicle fusion event classification	<a href="http://doi.org/10.1016/j.compmedig.2017.04.003">http://doi.org/10.1016/j.compmedig.2017.04.003</a>	C	FL	CL	Automated classification and tracking of vesicle fusion events in fluorescence microscopy image sequences using a novel hierarchical CNN.
230	Li Hen et al.	Cell Dynamic Morphology Classification Using Deep Convolutional Neural Networks	<a href="https://doi.org/10.1002/cyto.a.23490">https://doi.org/10.1002/cyto.a.23490</a>	C	BF	CL	Mouse lymphocytes cell dynamic morphology classification using a CNN classifier
231	Li R et al.	Deep Learning Segmentation of Optical Microscopy Images Improves 3-D Neuron Reconstruction	<a href="http://doi.org/10.1109/TMI.2017.2679713">http://doi.org/10.1109/TMI.2017.2679713</a>	S	BF	CL	Improved voxel-wise segmentation of volumetric neuronal microscopy images using a novel 3D CNN.
232	Li Y et al.	DLBI: Deep learning guided Bayesian inference for structure reconstruction of super-resolution fluorescence microscopy	<a href="http://doi.org/10.1093/bioinformatics/bty241">http://doi.org/10.1093/bioinformatics/bty241</a>	P	FL	SB	Time-series analysis and visualization of subcellular structures using a bayesian multi-scale CNN.
233	Liang L et al.	A deep learning approach to estimate chemically-treated collagenous tissue nonlinear anisotropic stress-strain responses from microscopy images	<a href="http://doi.org/10.1016/j.actbio.2017.09.025">http://doi.org/10.1016/j.actbio.2017.09.025</a>	C	FL	T	GLBP tissue elastic properties prediction in non-invasive second harmonic generation (SHG) images of collagen networks using CNN classifier.
234	Liu K et al.	Fast 3D cell tracking with wide-field fluorescence microscopy through deep learning	<a href="http://arxiv.org/abs/1805.05139v2">http://arxiv.org/abs/1805.05139v2</a>	C	FL	CL	Prediction of 3D locations from a single 2D fluorescence microscopy image by cascading two CNN's for in vivo 3D tracking of multiple blood cells.
235	López YP et al.	Automatic classification of light field smear microscopy patches using Convolutional Neural Networks for identifying Mycobacterium Tuberculosis	<a href="http://doi.org/10.1109/DISTR.A.2017.8229512">http://doi.org/10.1109/DISTR.A.2017.8229512</a>	C	BF	CL	Identification of Mycobacterium tuberculosis by classifying light field smear microscopy images using augmented input patches for a CNN classifier.
236	Lu A et al.	Learning unsupervised feature representations for single cell microscopy images with paired cell inpainting	<a href="https://doi.org/10.1101/395954">https://doi.org/10.1101/395954</a>	C	FL	CL	Improved phenotypic classification for both yeast and human cells using an unsupervised CNN classifier.
237	Maitin-Shepard J et al.	Combinatorial Energy Learning for Image Segmentation	<a href="http://arxiv.org/abs/1506.04304v3">http://arxiv.org/abs/1506.04304v3</a>	S	EM	T	Segmentation of neuropil tissues using a CNN to model the conditional energy of a segmentation output.
238	Marsh JN et al.	Deep Learning Global Glomerulosclerosis in Transplant Kidney Frozen Sections	<a href="https://doi.org/10.1101/292789">https://doi.org/10.1101/292789</a>	C	BF	T,CL	Automated identification and classification of glomeruli in frozen donor kidney section biopsies whole-slide images using a CNN model
239	Matuszewski DJ et al.	Minimal annotation training for segmentation of microscopy images	<a href="http://doi.org/10.1109/ISBI.2018.8363599">http://doi.org/10.1109/ISBI.2018.8363599</a>	S	EM	CL	Improved segmentation of viruses in EM images with minimal annotation using a U-Net model.
240	Mesbah R et al.	Deep convolutional encoder-decoder for myelin and axon segmentation	<a href="http://doi.org/10.1109/IVCNZ.2016.7804455">http://doi.org/10.1109/IVCNZ.2016.7804455</a>	S	BF	SB	Automated segmentation of myelin and axon from mouse spinal cord microscopy images using CNN and Convolutional autoencoder.
241	Mishra M et al.	Structure-based assessment of cancerous mitochondria using deep networks	<a href="http://doi.org/10.1109/ISBI.2016.7493327">http://doi.org/10.1109/ISBI.2016.7493327</a>	C	EM	SB	Automated quantitative assessment of mitochondria structures isolated from liver tumor cell lines using a CNN classifier.
242	Murthy V et al.	Center-Focusing Multi-task {CNN} with Injected Features for Classification of Glioma Nuclear Images	<a href="https://doi.org/10.1109%2Fwacv.2017.98">https://doi.org/10.1109%2Fwacv.2017.98</a>	C	BF	CL	Automated shapes and attributes classification of a glioma cell nucleus using a CNN classifier.



243	Naito T et al.	Identification and segmentation of myelinated nerve fibers in a cross-sectional optical microscopic image using a deep learning model	<a href="http://doi.org/10.1016/j.jneumeth.2017.08.014">http://doi.org/10.1016/j.jneumeth.2017.08.014</a>	S	BF	T	Automated nerve fiber identification and segmentation using CNN model.
244	Nanni L et al.	Bioimage Classification with Handcrafted and Learned Features	<a href="http://doi.org/10.1109/TCBB.2018.2821127">http://doi.org/10.1109/TCBB.2018.2821127</a>	C	BF,FL	CL,SB	Generic bioimage classification method for a wide range of cell and subcellular classification problems using a CNN model.
245	Nazeri K et al.	Two-Stage Convolutional Neural Network for Breast Cancer Histology Image Classification	<a href="http://doi.org/10.1007/978-3-319-93000-8_81">http://doi.org/10.1007/978-3-319-93000-8_81</a>	C	BF	T	Automated detection and classification of breast tissue in microscopy images using multiple patch-based CNN classifiers.
246	Nguyen T et al.	A deep-learning approach for high-speed Fourier ptychographic microscopy	<a href="http://doi.org/10.1364/3D.2018.JTh3A.6">http://doi.org/10.1364/3D.2018.JTh3A.6</a>	P	BF	CL	Automated reconstruction of dynamic live cells video sequence captured using a computational microscopy technique using a CNN model.
247	Nguyen T et al.	Deep learning bi-telecentric digital holographic microscopy for aberration compensation applied to cancer cells	<a href="http://doi.org/10.1364/DH.2017.Tu2A.5">http://doi.org/10.1364/DH.2017.Tu2A.5</a>	P	BF	CL	Automated background area detection for residual phase aberration compensation using a CNN model.
248	Nie W-Z et al.	3D Convolutional Networks-Based Mitotic Event Detection in Time-Lapse Phase Contrast Microscopy Image Sequences of Stem Cell Populations	<a href="http://doi.org/10.1109/CVPRW.2016.171">http://doi.org/10.1109/CVPRW.2016.171</a>	C	BF	CL	Automated mitotic event detection of stem cell populations in time-lapse phase contrast microscopy images using a CNN classifier.
249	Nioka H et al.	Classification of C2C12 cells at differentiation by convolutional neural network of deep learning using phase contrast images	<a href="http://doi.org/10.1007/s13577-017-0191-9">http://doi.org/10.1007/s13577-017-0191-9</a>	C	BF	CL	Automated cellular differentiation recognition of myogenic C2C12 cell line with phase contrast microscopy using a CNN classifier.
250	Nishimoto S et al.	Predicting the future direction of cell movement with convolutional neural networks	<a href="https://doi.org/10.1101/388033">https://doi.org/10.1101/388033</a>	C	BF	CL	Automated cell migration prediction from a single image patch of a cell at a particular time using multiple CNN's.
251	Nyawira I et al.	Understanding neural pathways in zebrafish through deep learning and high resolution electron microscope data	<a href="http://doi.org/10.1145/3219104.3229285">http://doi.org/10.1145/3219104.3229285</a>	S	EM	SB	Automated segmentation of high-resolution scanning electron microscope (SEM) image data using a CNN model.
252	Ounkomol C et al.	Three dimensional cross-modal image inference: label-free methods for subcellular structure prediction	<a href="https://doi.org/10.1101/216606">https://doi.org/10.1101/216606</a>	C	FL, BF	SB	Automated prediction of fluorescently labeled structures in live cells solely from 3D brightfield microscopy images using CNN classifier.
253	Ounkomol C et al.	Label-free prediction of three-dimensional fluorescence images from transmitted light microscopy	<a href="https://doi.org/10.1101/289504">https://doi.org/10.1101/289504</a>	C	FL	CL	Prediction of 3D fluorescence directly from transmitted light images using a CNN classifier for generating multi-structure, integrated images.
254	Oztel I et al.	Mitochondria segmentation in electron microscopy volumes using deep convolutional neural network	<a href="http://doi.org/10.1109/BIBM.2017.8217827">http://doi.org/10.1109/BIBM.2017.8217827</a>	S	EM	SB	Automated segmentation of mitochondria in the CA1 hippocampus region of brain tissue from electron microscopy images using CNN model.
255	Öztürk Ş et al.	A convolutional neural network model for semantic segmentation of mitotic events in microscopy images	<a href="http://doi.org/10.1007/s00521-017-3333-9">http://doi.org/10.1007/s00521-017-3333-9</a>	S	BF, EM	CL	Improved mitosis segmentation using CNN model for Semantic segmentation.
256	Pahariya G et al.	High precision automated detection of labeled nuclei in terabyte-scale whole-brain volumetric image data of mouse	<a href="https://doi.org/10.1101/252247">https://doi.org/10.1101/252247</a>	C	FL	CL	Automated mitosis detection by aggregating data using CNN via additional crowdsourcing layer (AggNet).
257	Pan X et al.	Cell detection in pathology and microscopy images with multi-scale fully convolutional neural networks	<a href="http://doi.org/10.1007/s11280-017-0520-7">http://doi.org/10.1007/s11280-017-0520-7</a>	C	BF,FL	CL	Automated density map regression to robustly detect the nuclei in pathology and microscopy images using a novel multi-scale CNN classifier.
258	Panicker RO et al.	Automatic detection of tuberculosis bacilli from microscopic sputum smear images using deep learning methods	<a href="http://doi.org/10.1016/j.bbe.2018.05.007">http://doi.org/10.1016/j.bbe.2018.05.007</a>	C	BF	CL	Automated detection of tuberculosis (TB) bacilli from microscopic sputum smear images using a CNN classifier.
259	Penas KED et al.	Malaria Parasite Detection and Species Identification on Thin Blood Smears Using a Convolutional Neural Network	<a href="http://doi.org/10.1109/CHAS E.2017.51">http://doi.org/10.1109/CHAS E.2017.51</a>	C	BF	SB	Automated detection of malaria parasites in thin blood smears images using a CNN classifier.
260	Pitkäaho T et al.	Performance of autofocus capability of deep convolutional neural networks in digital holographic microscopy	<a href="http://doi.org/10.1364/DH.2017.W2A.5">http://doi.org/10.1364/DH.2017.W2A.5</a>	P	BF	CL	Automated focusing of digital holograms of microscopic objects using a CNN model.
261	Qiao H et al.	GPU-based deep convolutional neural network for tomographic phase microscopy with $\ell_1$ fitting and regularization	<a href="http://doi.org/10.1117/1.JBO.23.6.066003">http://doi.org/10.1117/1.JBO.23.6.066003</a>	P	O	CL	Improve the performance of phase tomography using a CNN model.

262	Qiu Y et al.	Applying deep learning technology to automatically identify metaphase chromosomes using scanning microscopic images: An initial investigation	<a href="http://doi.org/10.1117/12.2217418">http://doi.org/10.1117/12.2217418</a>	C	FL	SB	Identification of chromosomes metaphase sub-cellular structures using a CNN classifier.
263	Quan TM et al.	FusionNet: A deep fully residual convolutional neural network for image segmentation in connectomics	<a href="http://arxiv.org/abs/1612.05360v2">http://arxiv.org/abs/1612.05360v2</a>	S	EM	T,CL	Automated segmentation of neuronal structures in connectomics data using a CNN model.
264	Quay M et al.	Designing deep neural networks to automate segmentation for serial block-face electron microscopy	<a href="http://doi.org/10.1109/ISBI.2018.8363603">http://doi.org/10.1109/ISBI.2018.8363603</a>	S	EM	CL,SB	Automated segmentation of a human platelet tissue sample in serial block-face electron microscopy images using an ensemble of CNN model.
265	Quinn JA et al.	Deep Convolutional Neural Networks for Microscopy-Based Point of Care Diagnostics	<a href="http://arxiv.org/abs/1608.02989v1">http://arxiv.org/abs/1608.02989v1</a>	C	BF	CL	Automated diagnosis of malaria in thick blood smears, tuberculosis in sputum samples, and intestinal parasite eggs using a CNN model.
266	Rajasekaran K et al.	An accurate perception method for low contrast bright field microscopy in heterogeneous microenvironments	<a href="http://doi.org/10.3390/app7121327">http://doi.org/10.3390/app7121327</a>	C	BF	SB	Automated perceiving of shapes for optical tweezers-based robotic manipulation using a CNN classifier.
267	Rakhlin A et al.	Deep Convolutional Neural Networks for Breast Cancer Histology Image Analysis	<a href="http://doi.org/10.1007/978-3-319-93000-8_83">http://doi.org/10.1007/978-3-319-93000-8_83</a>	C	BF	T	Automated classification of breast cancer tissues in histology images using a CNN classifier.
268	Rao Q et al.	Automatically segmenting and reconstructing neurons in SEM images	<a href="http://doi.org/10.1109/ICMA.2016.7558857">http://doi.org/10.1109/ICMA.2016.7558857</a>	S	EM	CL	Neuronal boundary detection and segmentation using membrane detection probability map (MDPM) generated by a CNN model.
269	Rao Q et al.	Deep learning and shapes similarity for joint segmentation and tracing single neurons in SEM images	<a href="http://doi.org/10.1117/12.2254284">http://doi.org/10.1117/12.2254284</a>	S	EM	CL	Automated neuronal membranes detection from Tape-collecting Ultra Microtome Scanning Electron Microscopy (ATUM-SEM) using a CNN model.
270	Ravi D et al.	Effective deep learning training for single-image super-resolution in endomicroscopy exploiting video-registration-based reconstruction	<a href="http://doi.org/10.1007/s11548-018-1764-0">http://doi.org/10.1007/s11548-018-1764-0</a>	P	FL	CL	Improved image superresolution reconstruction using a novel synthetic data generation approach to train the exemplar-based CNN model.
271	Raza SEA et al.	Micro-Net: A unified model for segmentation of various objects in microscopy images	<a href="http://arxiv.org/abs/1804.08145v1">http://arxiv.org/abs/1804.08145v1</a>	S	FL, BF	CL, SB	Automated segmentation of cells, nuclei, and glands in fluorescence microscopy and histology images using a multi-resolution CNN model.
272	Raza SEA et al.	MIMO-Net: A multi-input multi-output convolutional neural network for cell segmentation in fluorescence microscopy images	<a href="http://doi.org/10.1109/ISBI.2017.7950532">http://doi.org/10.1109/ISBI.2017.7950532</a>	S	FL	CL	Automated cell segmentation in fluorescence microscopy images using multiple-input-multiple-output CNN model.
273	Rempfler M et al.	Tracing cell lineages in videos of lens-free microscopy	<a href="http://doi.org/10.1016/j.media.2018.05.009">http://doi.org/10.1016/j.media.2018.05.009</a>	C	BF	CL	Automated detection and tracking of cells in LFM images using a CNN model and probabilistic model based on moral lineage tracing.
274	Ren J et al.	Adversarial Domain Adaptation for Classification of Prostate Histopathology Whole-Slide Images	<a href="https://arxiv.org/abs/1806.01357">https://arxiv.org/abs/1806.01357</a>	C	BF	T	Improved classification for automated Gleason grading of prostate histopathology tissue Whole-Slide Images using adversarial domain adaptation.
275	Rezaeilouyeh H et al.	Microscopic medical image classification framework via deep learning and shearlet transform	<a href="http://doi.org/10.1117/1.JMI.3.4.044501">http://doi.org/10.1117/1.JMI.3.4.044501</a>	C	BF	T	Automated cancer tissue diagnosis using magnitude and phase of shearlet coefficients as additional input for a CNN classifier.
276	Rivenson Y et al.	Phase recovery and holographic image reconstruction using deep learning in neural networks	<a href="https://doi.org/10.1038/lsa.2017.141">https://doi.org/10.1038/lsa.2017.141</a>	P	BF	T	Improved phase retrieval and holographic image reconstruction of blood, Pap smears, and tissue sections using a cascaded multi-scale CNN model.
277	Rivenson Y et al.	Toward a Thinking Microscope: Deep Learning in Optical Microscopy and Image Reconstruction	<a href="http://arxiv.org/abs/1805.08970v1">http://arxiv.org/abs/1805.08970v1</a>	P	BF	T	Automated microscopic image reconstruction of lung, kidney, and breast tissue sections using a CNN model.
278	Rivenson Y et al.	PhaseStain: Digital staining of label-free quantitative phase microscopy images using deep learning	<a href="http://arxiv.org/abs/1807.07701v1">http://arxiv.org/abs/1807.07701v1</a>	P	BF	T	Virtual staining for brightfield microscopy images of skin, kidney, and liver tissue sections using a generative adversarial network (GAN) model.
279	Robitaille L et al.	Learning to Become an Expert: Deep Networks Applied To Super-Resolution Microscopy	<a href="http://arxiv.org/abs/1803.10806v1">http://arxiv.org/abs/1803.10806v1</a>	P	STED	T	An automated quantitative quality measure of neuronal structures in super-resolution microscopy images using a CNN model.
280	Roels J et al.	Convolutional neural network pruning to accelerate membrane segmentation in electron microscopy	<a href="http://doi.org/10.1109/ISBI.2017.7950600">http://doi.org/10.1109/ISBI.2017.7950600</a>	S	EM	SB	Improved membrane segmentation of mitochondria and endoplasmic reticula by optimizing a CNN model.
281	Romo-Bucheli D et al.	A deep learning based strategy for identifying and associating mitotic activity with gene expression derived risk categories in estrogen receptor positive breast cancers	<a href="https://doi.org/10.1002/cyto.a.23065">https://doi.org/10.1002/cyto.a.23065</a>	C	BF	T	Improved mitotic figures identification from breast cancer tissue whole slides images using a CNN classifier.
282	Sabbaghi S et al.	A deep bag-of-features model for the classification of melanomas in dermoscopy images	<a href="http://doi.org/10.1109/EMBC.2016.7590962">http://doi.org/10.1109/EMBC.2016.7590962</a>	C	BF	CL	Classification of cancer and non-cancer skin regions using a stacked sparse auto-encoder with SIFT and color descriptors.

283	Sailem H et al.	Discovery of Rare Phenotypes in Cellular Images Using Weakly Supervised Deep Learning	<a href="http://doi.org/10.1109/ICCVW.2017.13">http://doi.org/10.1109/ICCVW.2017.13</a>	P	FL	CL	Automated labeling of genetically weak perturbed cells phenotypes using a weakly supervised CNN to identify rare events location.
284	Saponaro P et al.	DeepXScope: Segmenting Microscopy Images with a Deep Neural Network	<a href="http://doi.org/10.1109/CVPRW.2017.117">http://doi.org/10.1109/CVPRW.2017.117</a>	S	FL	T	Automated segmenting of the fungal pathogen and cell boundaries and stomata of the host plant tissues using a CNN model.
285	Schaumberg AJ et al.	DeepScope: Nonintrusive Whole Slide Saliency Annotation and Prediction from Pathologists at the Microscope	<a href="https://doi.org/10.1101/097246">https://doi.org/10.1101/097246</a>	C	BF	T	Creation of whole-slide image saliency maps to facilitate manual annotation process using a pre-trained CNN classifier.
286	Schaumberg AJ et al.	H&E-stained Whole Slide Image Deep Learning Predicts SPOP Mutation State in Prostate Cancer	<a href="https://doi.org/10.1101/064279">https://doi.org/10.1101/064279</a>	C	BF	T	Prediction of a genetic mutation (SPOP) in whole slide images of prostate cancer tissues using a CNN classifier.
287	Schaumberg AJ et al.	Large-Scale Annotation of Histopathology Images from Social Media	<a href="https://doi.org/10.1101/396663">https://doi.org/10.1101/396663</a>	C	BF	T	Classification of several tissue types from a dataset created from images shared by pathologists on twitter using pre-trained CNN classifiers.
288	Schubert P et al.	Learning cellular morphology with neural networks	<a href="https://doi.org/10.1101/364034">https://doi.org/10.1101/364034</a>	S	EM	SB	Automated reconstruction and detection of cellular fragments in volumetric brain tissue images by multi-view CNN model.
289	Shahbazi A et al.	Flexible Learning-Free Segmentation and Reconstruction for Sparse Neuronal Circuit Tracing	<a href="https://doi.org/10.1101/278515">https://doi.org/10.1101/278515</a>	S	EM	CL	Creation of a learning-free method for sparse segmentation and reconstruction of neural volumes using a CNN model.
290	Sheikhzadeh F et al.	Automatic labeling of molecular biomarkers of immunohistochemistry images using fully convolutional networks	<a href="http://doi.org/10.1371/journal.pone.0190783">http://doi.org/10.1371/journal.pone.0190783</a>	C	BF	T	Automated detection and classification of molecular biomarkers of tissues using a CNN classifier.
291	Shen W et al.	Multi-stage Multi-recursive-input Fully Convolutional Networks for Neuronal Boundary Detection	<a href="http://arxiv.org/abs/1703.08493v2">http://arxiv.org/abs/1703.08493v2</a>	S	EM	T	Identification of cortical connectivity by improved mouse piriform cortex image segmentation using a multi-stage multi-recursive CNN model.
292	Shkolyar A et al.	Automatic detection of cell divisions (mitosis) in live-imaging microscopy images using Convolutional Neural Networks	<a href="http://doi.org/10.1109/EMBC.2015.7318469">http://doi.org/10.1109/EMBC.2015.7318469</a>	C	BF	CL	Semi-automated workflow for cell divisions detection in live-imaging microscopy by classifying mitosis candidates using a CNN classifier.
293	Sibley AR et al.	Simultaneous segmentation and classification of multichannel immuno-fluorescently labeled confocal microscopy images using deep convolutional neural networks	<a href="http://doi.org/10.1117/12.2292934">http://doi.org/10.1117/12.2292934</a>	S,C	FL	T	Automated segmentation and classification of dendritic cell types for application to cell membrane immunofluorescent stains using a CNN model.
294	Singh SP et al.	Machine learning based classification of cells into chronological stages using single-cell transcriptomics.	<a href="https://doi.org/10.1101/303214">https://doi.org/10.1101/303214</a>	C	FL	CL	Detection of premature aging in cells using a CNN classifier to provide a window for preventive therapies against age-related diseases.
295	Sirinukunwattana K et al.	Locality Sensitive Deep Learning for Detection and Classification of Nuclei in Routine Colon Cancer Histology Images	<a href="https://doi.org/10.1109/tmi.2016.2525803">https://doi.org/10.1109/tmi.2016.2525803</a>	C	BF	T	Per-pixel likelihood prediction for improved nuclei detection in colon cancer histology images using a novel spatially constrained CNN classifier.
296	Smith KP et al.	Automated interpretation of blood culture gram stains by use of a deep convolutional neural network	<a href="http://doi.org/10.1128/JCM.01521-17">http://doi.org/10.1128/JCM.01521-17</a>	C	BF	T	Automated image acquisition and classification of Gram stain using a CNN classifier.
297	Song Y et al.	Accurate segmentation of cervical cytoplasm and nuclei based on multiscale convolutional network and graph partitioning	<a href="http://doi.org/10.1109/TBME.2015.2430895">http://doi.org/10.1109/TBME.2015.2430895</a>	S	BF	CL	Accurate segmentation of cervical cells of Cervical Cytoplasm and Nuclei using a multiscale CNN and graph-partitioning-based method.
298	Stegmaier J et al.	Cell segmentation in 3D confocal images using supervoxel merge-forests with CNN-based hypothesis selection	<a href="http://doi.org/10.1109/ISBI.2018.8363598">http://doi.org/10.1109/ISBI.2018.8363598</a>	S	FL	T	Automated segmentation of cell plants (meristem) clusters in volumetric microscopy images using a novel super-voxel CNN model.
299	Suleymanova I et al.	A deep convolutional neural network approach for astrocyte detection	<a href="https://doi.org/10.1101/241505">https://doi.org/10.1101/241505</a>	C	BF	CL	Fast and fully automated software for assessing the number of astrocytes using a CNN classifier.
300	tefko MÅ et al.	Design Principles for Autonomous Illumination Control in Localization Microscopy	<a href="https://doi.org/10.1101/295519">https://doi.org/10.1101/295519</a>	S	FL	SB	Automated molecule density estimation by fluorescence spot segmentation and counting using a CNN model.
301	Thierbach K et al.	Combining Deep Learning and Active Contours Opens The Way to Robust Automated Analysis of Brain Cytoarchitectonics	<a href="https://doi.org/10.1101/297689">https://doi.org/10.1101/297689</a>	S	FL	CL	Improved segmentation of neural cell bodies from volumetric light-sheet microscopy using a CNN model.
302	Tokuoka Y et al.	Convolutional Neural Network-Based Instance Segmentation Algorithm to Acquire Quantitative Criteria of Early Mouse Development	<a href="https://doi.org/10.1101/324186">https://doi.org/10.1101/324186</a>	S	FL	CL	Creation of a deep learning pipeline that segments each nucleus and adds different labels to the detected objects.

303	Tschopp F et al.	Efficient convolutional neural networks for pixelwise classification on heterogeneous hardware systems	<a href="http://doi.org/10.1109/ISBI.2016.7493487">http://doi.org/10.1109/ISBI.2016.7493487</a>	C	EM	T	<b>Transformation of a classification CNN to a segmentation NN to increase speed of predictions.</b>
304	Van Valen DA et al.	Deep Learning Automates the Quantitative Analysis of Individual Cells in Live-Cell Imaging Experiments	<a href="http://doi.org/10.1371/journal.pcbi.1005177">http://doi.org/10.1371/journal.pcbi.1005177</a>	S	BF	CL	<b>Improved bacterial and mammalian cells nuclei segmentation in fluorescent and phase images of the cytoplasm using CNN model.</b>
305	Vicar T et al.	Label-free nuclear staining reconstruction in quantitative phase images using deep learning	<a href="http://doi.org/10.1007/978-981-10-9035-6_43">http://doi.org/10.1007/978-981-10-9035-6_43</a>	P	BF, FL	CL, T	<b>Created artificial, fluorescence-like nuclei labeling from label-free images using CNNs.</b>
306	Vu QD et al.	Micro and Macro Breast Histology Image Analysis by Partial Network Re-use	<a href="http://doi.org/10.1007/978-3-319-93000-8_102">http://doi.org/10.1007/978-3-319-93000-8_102</a>	C, S	BF	T	<b>Improved classification and segmentation of breast cancer images by combining architectural components and weights of a CNN model.</b>
307	Wang C et al.	Edge Detection of Cryptic Lamellipodia Assisted by Deep Learning	<a href="https://doi.org/10.1101/181263">https://doi.org/10.1101/181263</a>	C	FL	CL	<b>Automated edges detection in time-lapse collective cell migration movies by combining traditional analysis methods with CNN models.</b>
308	Wang F et al.	DeepPicker: A deep learning approach for fully automated particle picking in cryo-EM	<a href="http://doi.org/10.1016/j.jsb.2016.07.006">http://doi.org/10.1016/j.jsb.2016.07.006</a>	C	EM	SB	<b>Improved classifications of target particles from multiple molecular complexes using an iterative CNN-based workflow.</b>
309	Wang Q et al.	Accurate and high throughput cell segmentation method for mouse brain nuclei using cascaded convolutional neural network	<a href="http://doi.org/10.1007/978-3-319-67434-6_7">http://doi.org/10.1007/978-3-319-67434-6_7</a>	S	FL	CL	<b>Improved segmentation by passing the probability map from one CNN as input to a subsequent CNN together with the original images.</b>
310	Wang Y et al.	Stem cell motion-tracking by using deep neural networks with multi-output	<a href="http://doi.org/10.1007/s00521-017-3291-2">http://doi.org/10.1007/s00521-017-3291-2</a>	C	BF	CL	<b>Automated mitosis detection and cell tracking using a CNN model with multiple outputs and a particle filter based sampling scheme.</b>
311	Wen C et al.	Deep-learning-based flexible pipeline for segmenting and tracking cells in 3D image time series for whole brain imaging	<a href="https://doi.org/10.1101/385567">https://doi.org/10.1101/385567</a>	C	FL	CL	<b>Pixel-wise classification of cells using a 3D U-Net model, followed by watershed cell segmentation, and tracking using a feed-forward network.</b>
312	Weng S et al.	Combining deep learning and coherent anti-Stokes Raman scattering imaging for automated differential diagnosis of lung cancer	<a href="http://doi.org/10.1117/1.JBO.22.10.106017">http://doi.org/10.1117/1.JBO.22.10.106017</a>	C	BF	T	<b>Classification of lung cancer tissue using pre-trained CNN classifiers.</b>
313	Wieslander H et al.	Deep Convolutional Neural Networks for Detecting Cellular Changes Due to Malignancy	<a href="https://doi.org/10.1109/iccvw.2017.18">https://doi.org/10.1109/iccvw.2017.18</a>	C	BF	CL	<b>Improved classification of oral and cervical cancer cells using pre-trained CNN models.</b>
314	Wollmann T et al.	Deep residual Hough voting for mitotic cell detection in histopathology images	<a href="http://doi.org/10.1109/ISBI.2017.7950533">http://doi.org/10.1109/ISBI.2017.7950533</a>	C	BF	CL	<b>Improved mitotic cell detection by combining the ResNet classifier with Hough voting method.</b>
315	Wollmann T et al.	Multi-channel deep transfer learning for nuclei segmentation in glioblastoma cell tissue images	<a href="http://doi.org/10.1007/978-3-662-56537-7_83">http://doi.org/10.1007/978-3-662-56537-7_83</a>	S	FL	CL	<b>Automated cell segmentation by combining atrous spatial pyramid pooling with a pre-trained U-Net model.</b>
316	Wu J et al.	Unsupervised single-particle deep clustering via statistical manifold learning	<a href="http://arxiv.org/abs/1604.04539v2">http://arxiv.org/abs/1604.04539v2</a>	C	EM	SB	<b>Unsupervised single-particle clustering using a manifold learning algorithm for deep learning model.</b>
317	Xiao C et al.	Deep contextual residual network for electron microscopy image segmentation in connectomics	<a href="http://doi.org/10.1109/ISBI.2018.8363597">http://doi.org/10.1109/ISBI.2018.8363597</a>	S	EM	CL, T	<b>Improved segmentation performance by utilizing multilevel contextual cues in a spatially efficient residual CNN model.</b>
318	Xiao C et al.	An effective fully deep convolutional neural networks for mitochondria segmentation based on ATUM-SEM	<a href="http://doi.org/10.1117/12.2293291">http://doi.org/10.1117/12.2293291</a>	S	EM	SB	<b>Robust mitochondrial segmentation by fusing multiple pre-trained CNN models.</b>
319	Xiao C et al.	Effective automated pipeline for 3D reconstruction of synapses based on deep learning	<a href="http://doi.org/10.1186/s12859-018-2232-0">http://doi.org/10.1186/s12859-018-2232-0</a>	C	EM	T	<b>Automated localization and detection of synapses using adapted faster region-CNN model.</b>
320	Xie Y et al.	Beyond Classification: Structured Regression for Robust Cell Detection Using Convolutional Neural Network	<a href="http://doi.org/10.1007/978-3-319-24574-4_43">http://doi.org/10.1007/978-3-319-24574-4_43</a>	C	BF	CL	<b>Automated detection of cells through encoded topological information using a final structured regression layer of a CNN classifier.</b>
321	Xie W et al.	Microscopy cell counting and detection with fully convolutional regression networks	<a href="http://doi.org/10.1080/21681163.2016.1149104">http://doi.org/10.1080/21681163.2016.1149104</a>	C	FL	CL	<b>Automated cell counting and detection using fully convolutional regression networks to estimate density maps</b>
322	Xu M et al.	A deep convolutional neural network for classification of red blood cells in sickle cell anemia	<a href="http://doi.org/10.1371/journal.pcbi.1005746">http://doi.org/10.1371/journal.pcbi.1005746</a>	C	BF	CL	<b>Classification of individual red blood cells images using a patch-based CNN classifier.</b>
323	Xu YKT et al.	Deep learning for high-throughput quantification of oligodendrocyte ensheathment: a UNet architecture to extract multiple morphological parameters from individual cells	<a href="https://doi.org/10.1101/389932">https://doi.org/10.1101/389932</a>	S	BF, FL	SB	<b>Improved myelin segmentation within cells using a UNet architecture.</b>
324	Xue Y et al.	A novel framework to integrate convolutional neural network with compressed sensing for cell detection	<a href="http://doi.org/10.1109/ICIP.2017.8296696">http://doi.org/10.1109/ICIP.2017.8296696</a>	C	BF	CL	<b>Automated detection and localization of cells by combining compressed-sensing based output encoding with CNN classifier.</b>
325	Yang L et al.	BoxNet: Deep Learning Based Biomedical Image Segmentation Using Boxes Only Annotation	<a href="https://arxiv.org/abs/1806.00593">https://arxiv.org/abs/1806.00593</a>	S	BF, EM	CL, T	<b>Improved localization of structures by combining weakly supervised deep learning box annotation and grid search for a CNN model.</b>

326	Yi F et al.	Automated red blood cells extraction from holographic images using fully convolutional neural networks	<a href="http://doi.org/10.1364/BOE.8.004466">http://doi.org/10.1364/BOE.8.004466</a>	S	BF	CL	<b>Integration of FCN with marker-controlled watershed segmentation on red blood cells.</b>
327	Yoo I et al.	ssEMnet: Serial-section electron microscopy image registration using a spatial transformer network with learned features	<a href="http://doi.org/10.1007/978-3-319-67558-9_29">http://doi.org/10.1007/978-3-319-67558-9_29</a>	P	EM	T	<b>Automated image alignment by combining a spatial transformer network and a convolutional autoencoder.</b>
328	Yu C et al.	Acral melanoma detection using a convolutional neural network for dermoscopy images	<a href="http://doi.org/10.1371/journal.pone.0193321">http://doi.org/10.1371/journal.pone.0193321</a>	C	BF	T	<b>Automated detection of acral melanoma in dermoscopy images using pre-trained CNN classifiers.</b>
329	Yu H et al.	Phenotypic Antimicrobial Susceptibility Testing with Deep Learning Video Microscopy	<a href="http://doi.org/10.1021/acs.analchem.8b01128">http://doi.org/10.1021/acs.analchem.8b01128</a>	C	BF	CL	<b>Pathogen concentrations determination in static images containing single cell features of bacteria using a CNN classifier.</b>
330	Yu L et al.	Automated Melanoma Recognition in Dermoscopy Images via Very Deep Residual Networks	<a href="http://doi.org/10.1109/TMI.2016.2642839">http://doi.org/10.1109/TMI.2016.2642839</a>	C	BF	T	<b>Segmentation and classification of melanoma in dermoscopy images by integrating a very deep CNN with a very deep residual CNN classifier.</b>
331	Yuan Y et al.	Automatic Skin Lesion Segmentation Using Deep Fully Convolutional Networks with Jaccard Distance	<a href="http://doi.org/10.1109/TMI.2017.2695227">http://doi.org/10.1109/TMI.2017.2695227</a>	S	BF	T	<b>Improved skin lesion segmentation by combining Jaccard distance based loss function with a CNN for imbalanced foreground and background pixels.</b>
332	Zaimi A et al.	AxonDeepSeg: Automatic axon and myelin segmentation from microscopy data using convolutional neural networks	<a href="http://doi.org/10.1038/s41598-018-22181-4">http://doi.org/10.1038/s41598-018-22181-4</a>	S	EM	SB	<b>An open-source software package for axon and myelin segmentation of microscopic images using an adapted U-Net model.</b>
333	Zeng T et al.	DeepEM3D: approaching human-level performance on 3D anisotropic EM image segmentation	<a href="http://doi.org/10.1093/bioinformatics/btx188">http://doi.org/10.1093/bioinformatics/btx188</a>	S	EM	SB	<b>Improved volumetric neurite segmentation using a hybrid 3D-2D CNN model accounting for anisotropy.</b>
334	Zhang H et al.	High-throughput high-resolution Generated Adversarial Network Microscopy	<a href="http://arxiv.org/abs/1801.07330v1">http://arxiv.org/abs/1801.07330v1</a>	P	BF, FL	T, CL, SB	<b>Super-resolution reconstruction from a large field of view by combining GANs with wide-field light images.</b>
335	Zhou Y et al.	Cell mitosis detection using deep neural networks	<a href="http://doi.org/10.1016/j.knosys.2017.08.016">http://doi.org/10.1016/j.knosys.2017.08.016</a>	C	BF	CL	<b>Automatic identification of potential mitosis events using a CNN model and false-positive reduction using a 3D-CNN classifier.</b>
336	Zhou Z et al.	DeepNeuron: an open deep learning toolbox for neuron tracing	<a href="http://doi.org/10.1186/s40708-018-0081-2">http://doi.org/10.1186/s40708-018-0081-2</a>	C	BF	CL	<b>Improved detection and tracing of neurons in different image conditions using a DeepNeuron within CNN modules.</b>
337	Zhu R.	An Extended Type Cell Detection and Counting Method based on FCN	<a href="http://doi.org/10.1109/BIBE.2017.00-79">http://doi.org/10.1109/BIBE.2017.00-79</a>	C	BF, EM	CL	<b>Automated counting and detection of cells by utilizing a CNN model.</b>
338	Zhu Y et al.	A deep convolutional neural network approach to single-particle recognition in cryo-electron microscopy	<a href="http://doi.org/10.1186/s12859-017-1757-y">http://doi.org/10.1186/s12859-017-1757-y</a>	C	EM	SB	<b>Single-particle recognition from noisy cryo-EM micrographs using a recursively trained CNN classifier.</b>