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(54) **SYSTEM AND METHOD FOR MULTICLASS CLASSIFICATION OF IMAGES USING A PROGRAMMABLE LIGHT SOURCE**

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A61B 1/06 (2006.01)
G06K 9/62 (2006.01)
(Continued)

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None
See application file for complete search history.

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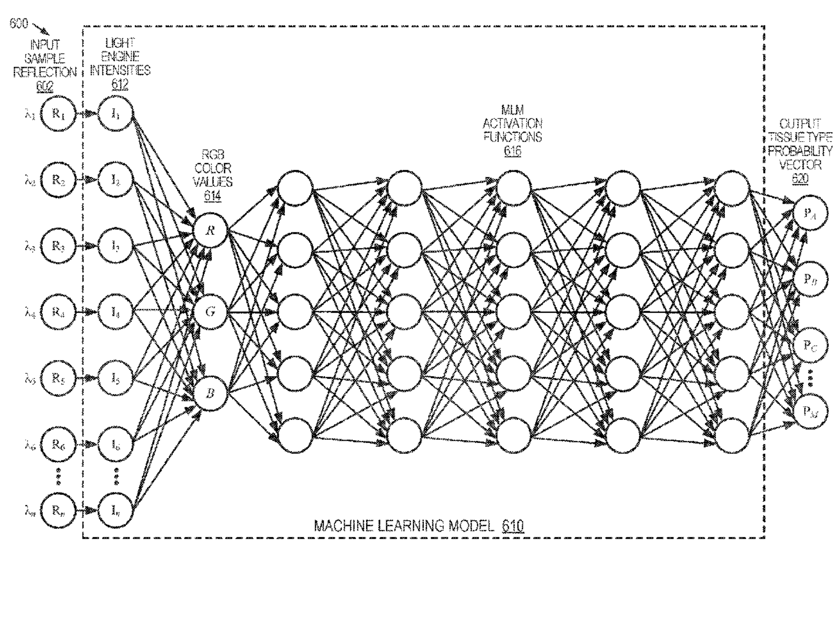
(74) *Attorney, Agent, or Firm* — Christensen O'Connor Johnson Kindness PLLC

(57) **ABSTRACT**

An apparatus, system and process for identifying one or more different tissue types are described. The method may include applying a configuration to one or more programmable light sources of an imaging system, where the configuration is obtained from a machine learning model trained to distinguish between the one or more different tissue types captured in image data. The method may also include illuminating a scene with the configured one or more programmable light sources, and capturing image data that includes one or more types of tissue depicted in the image data. Furthermore, the method may include analyzing color information in the captured image data with the machine learning model to identify at least one of the one or more different tissue types in the image data, and rendering a visualization of the scene from the captured image data that visually differentiates tissue types in the visualization.

20 Claims, 7 Drawing Sheets



(51) **Int. Cl.**

G06T 7/90	(2017.01)
G06K 9/20	(2006.01)
A61B 5/00	(2006.01)
G02B 23/24	(2006.01)
G06F 15/76	(2006.01)
A61B 1/00	(2006.01)
A61B 5/103	(2006.01)
A61B 1/04	(2006.01)
G06N 3/08	(2006.01)
A61B 1/005	(2006.01)
G06N 20/00	(2019.01)

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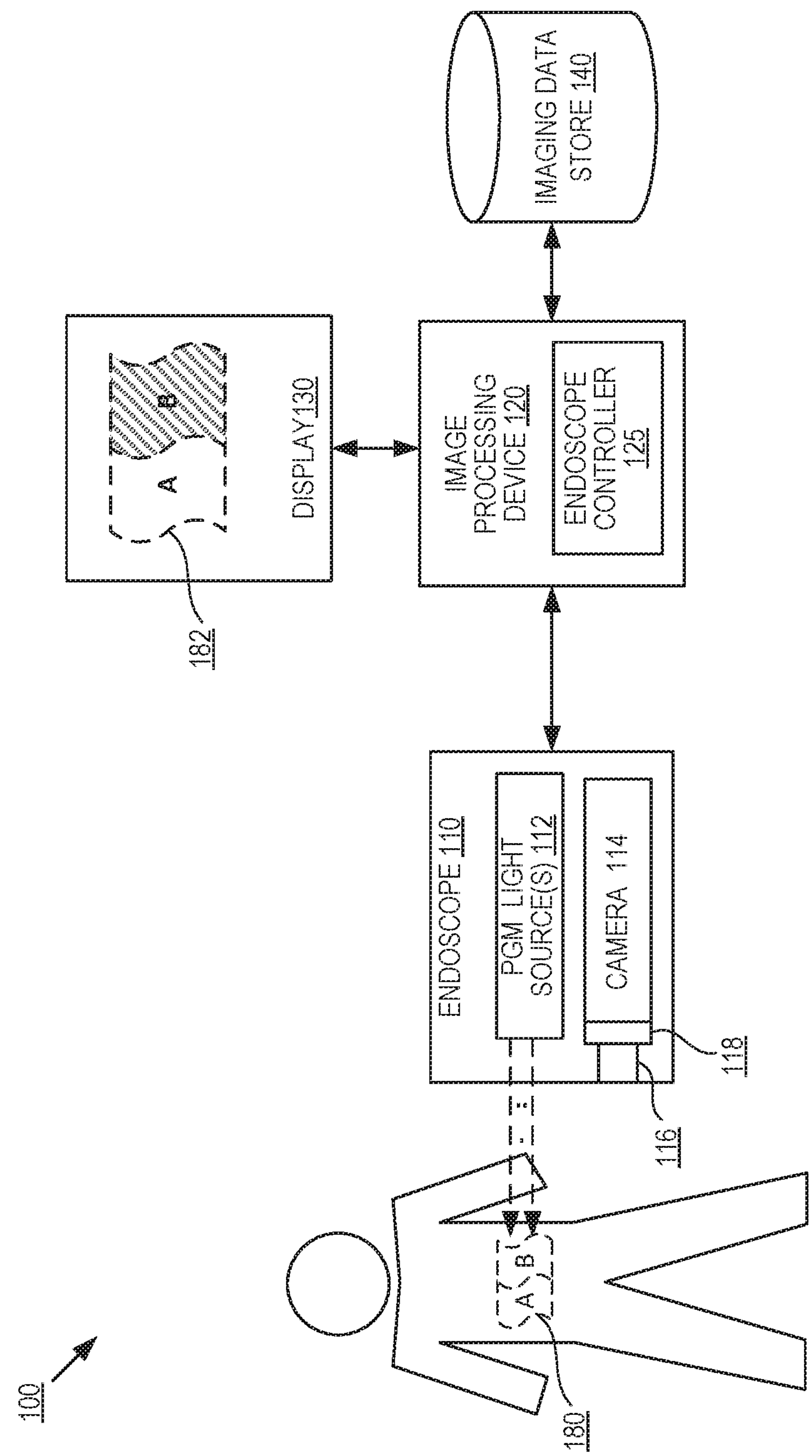

IMAGING DATA STORE 140
IMAGE PROCESSING DEVICE 120
ENDOSCOPE CONTROLLER 125
DISPLAY130
A
B
182
ENDOSCOPE 110
PGM LIGHT SOURCE(S) 112
CAMERA 114
118
116
A
B
180
100

FIG. 1

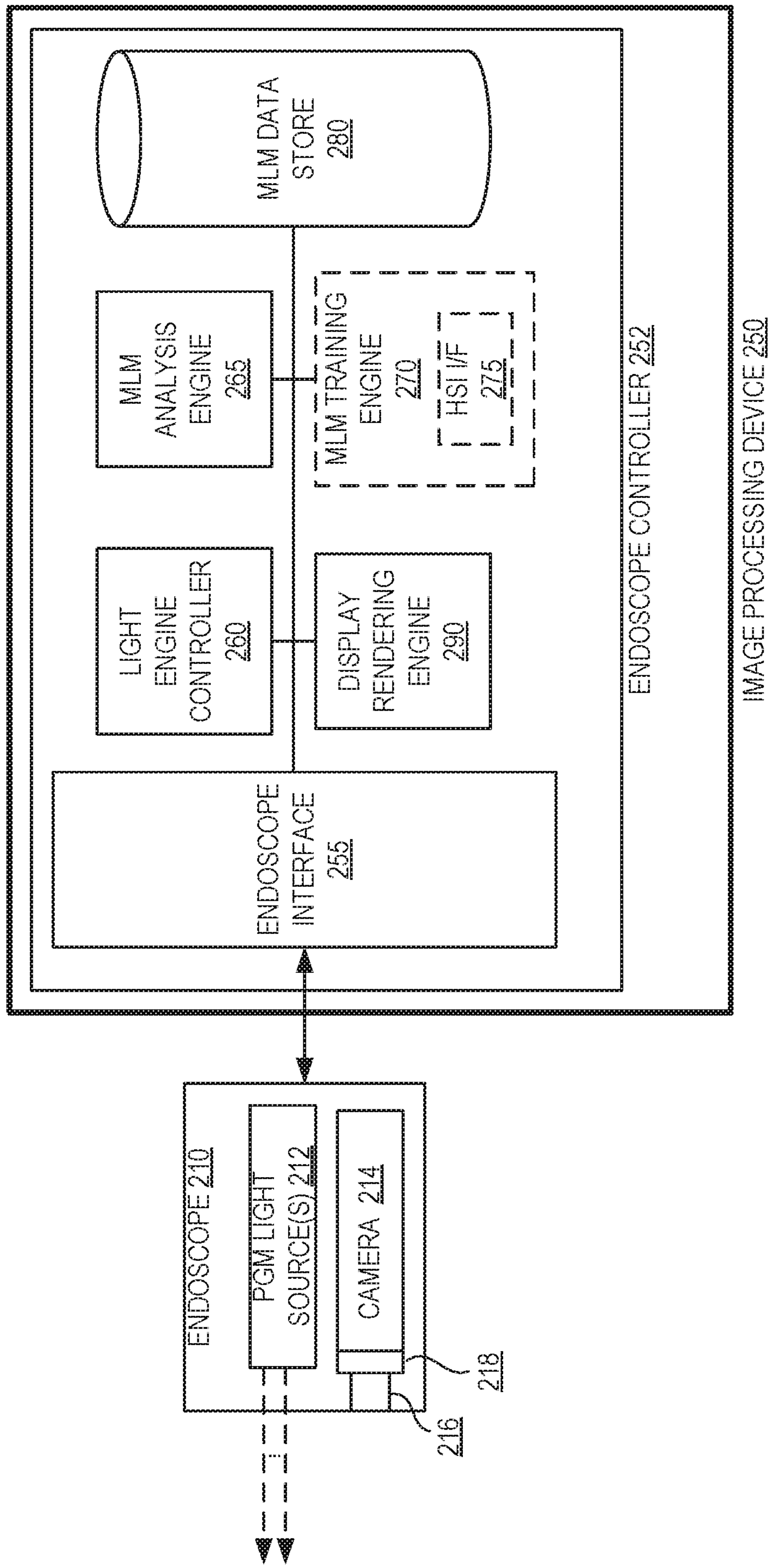

MLM DATA STORE 280
MLM ANALYSIS ENGINE 265
MLM TRAINING ENGINE 270
HSI I/F 275
LIGHT ENGINE CONTROLLER 260
DISPLAY RENDERING ENGINE 290
ENDOSCOPE INTERFACE 255
ENDOSCOPE CONTROLLER 252
IMAGE PROCESSING DEVICE 250
ENDOSCOPE 210
PGM LIGHT SOURCE(S) 212
CAMERA 214
218
216

FIG. 2

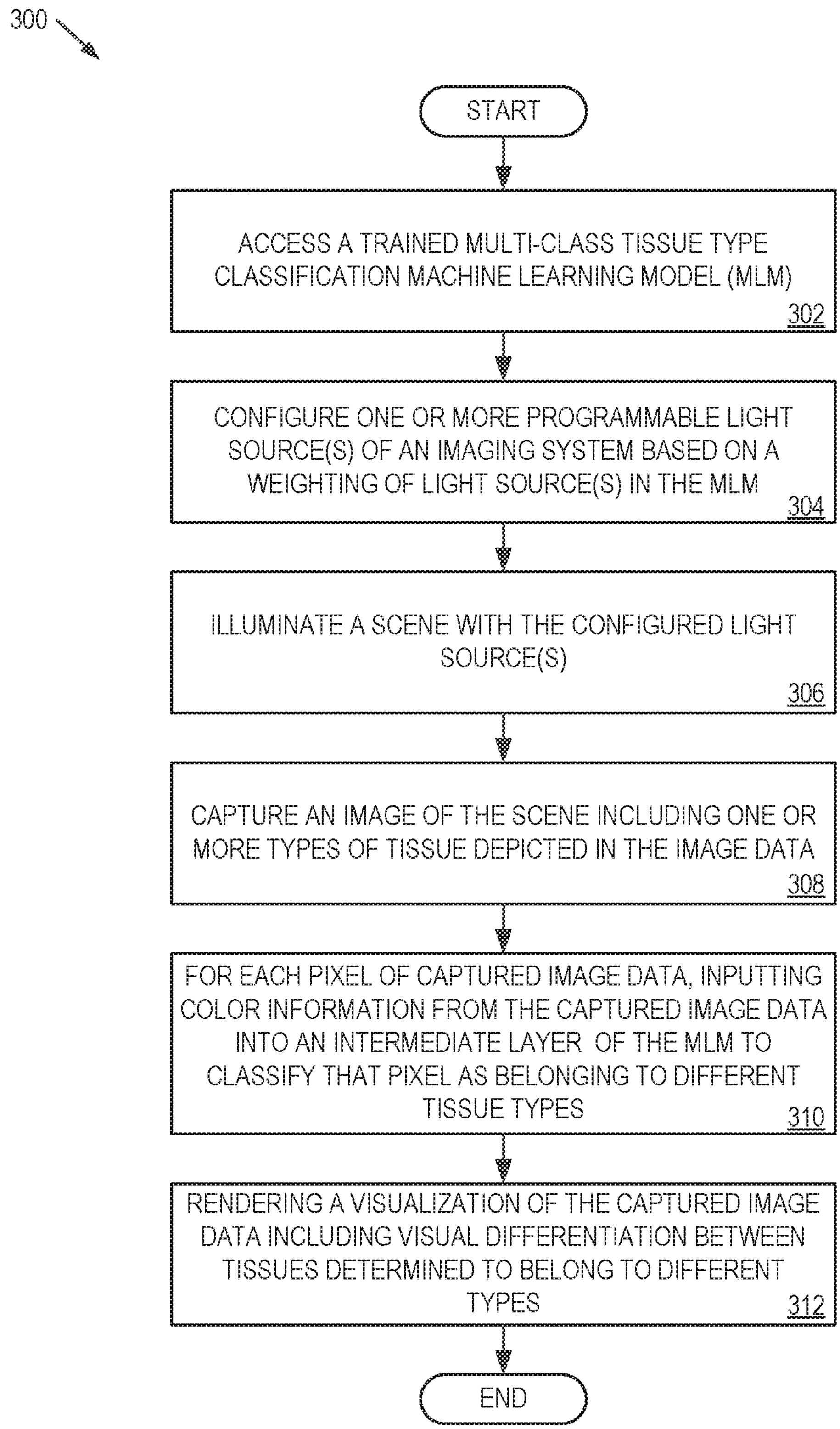

300
START
ACCESS A TRAINED MULTI-CLASS TISSUE TYPE CLASSIFICATION MACHINE LEARNING MODEL (MLM)
302
CONFIGURE ONE OR MORE PROGRAMMABLE LIGHT SOURCE(S) OF AN IMAGING SYSTEM BASED ON A WEIGHTING OF LIGHT SOURCE(S) IN THE MLM
304
ILLUMINATE A SCENE WITH THE CONFIGURED LIGHT SOURCE(S)
306
CAPTURE AN IMAGE OF THE SCENE INCLUDING ONE OR MORE TYPES OF TISSUE DEPICTED IN THE IMAGE DATA
308
FOR EACH PIXEL OF CAPTURED IMAGE DATA, INPUTTING COLOR INFORMATION FROM THE CAPTURED IMAGE DATA INTO AN INTERMEDIATE LAYER OF THE MLM TO CLASSIFY THAT PIXEL AS BELONGING TO DIFFERENT TISSUE TYPES
310
RENDERING A VISUALIZATION OF THE CAPTURED IMAGE DATA INCLUDING VISUAL DIFFERENTIATION BETWEEN TISSUES DETERMINED TO BELONG TO DIFFERENT TYPES
312
END

FIG. 3

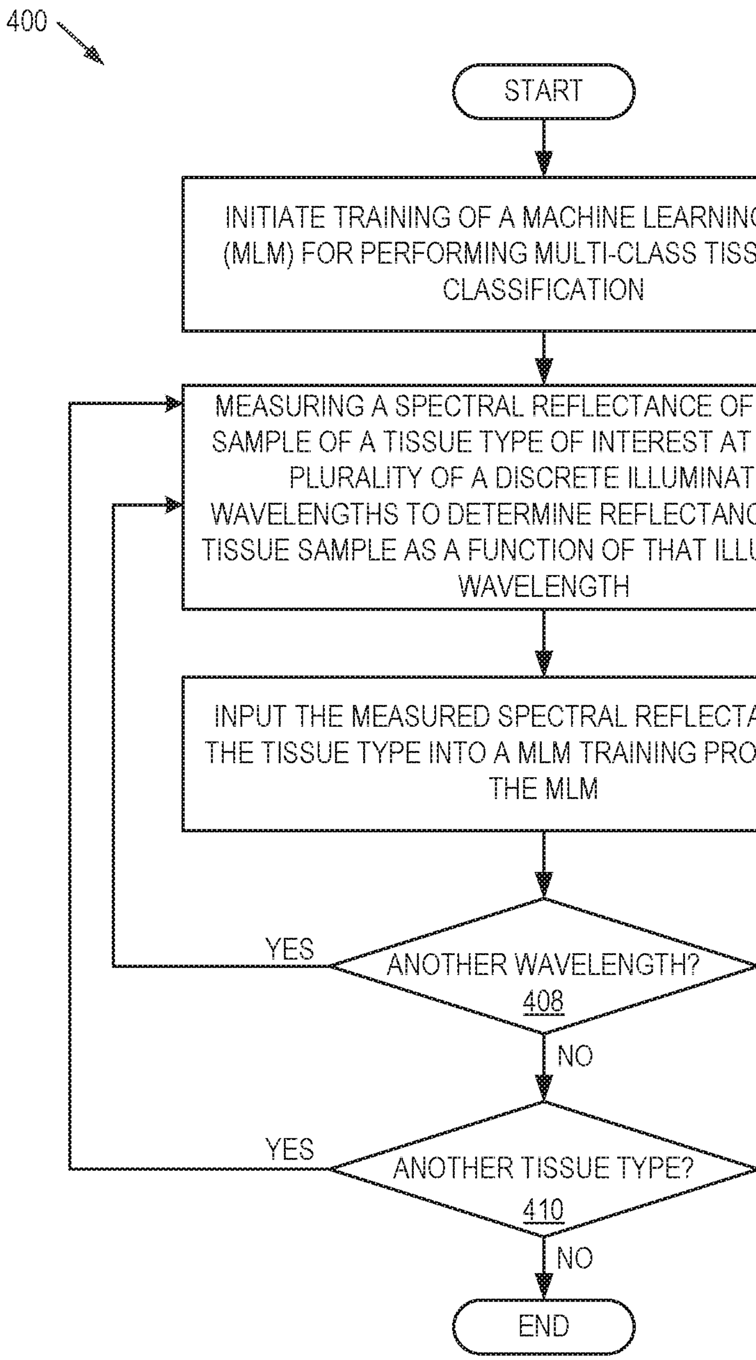

400
START
INITIATE TRAINING OF A MACHINE LEARNING MODEL (MLM) FOR PERFORMING MULTI-CLASS TISSUE TYPE CLASSIFICATION
402
MEASURING A SPECTRAL REFLECTANCE OF A TISSUE SAMPLE OF A TISSUE TYPE OF INTEREST AT ONE OF A PLURALITY OF A DISCRETE ILLUMINATION WAVELENGTHS TO DETERMINE REFLECTANCE OF THE TISSUE SAMPLE AS A FUNCTION OF THAT ILLUMINATION WAVELENGTH
404
INPUT THE MEASURED SPECTRAL REFLECTANCE FOR THE TISSUE TYPE INTO A MLM TRAINING PROCESS FOR THE MLM
406
YES
ANOTHER WAVELENGTH?
408
NO
YES
ANOTHER TISSUE TYPE?
410
NO
END

FIG. 4

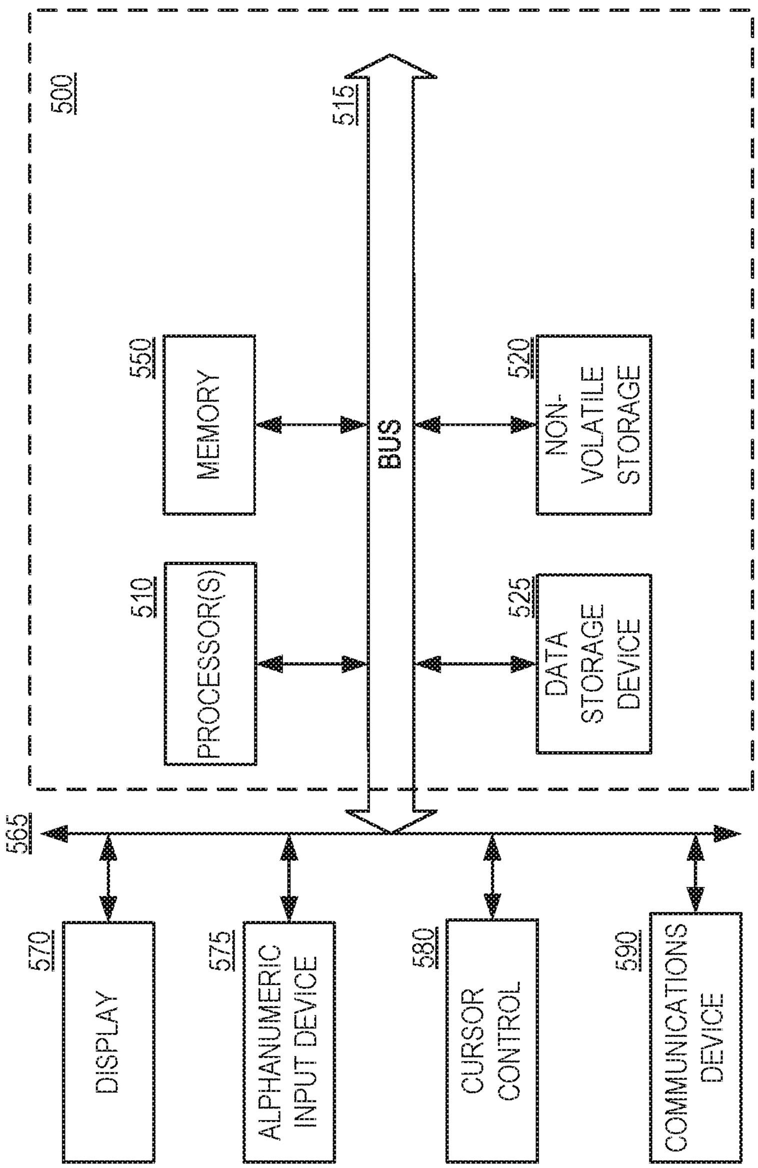
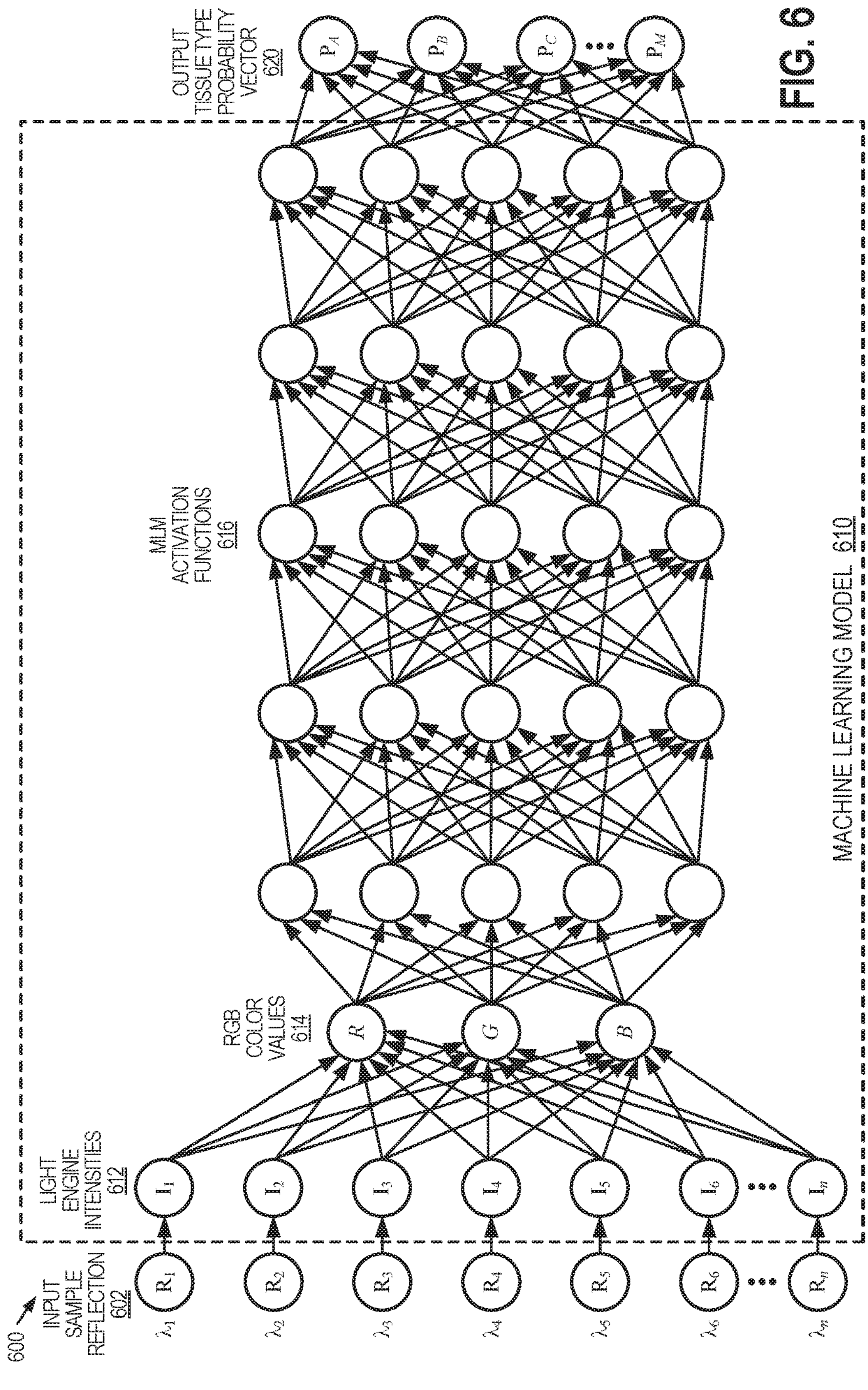

500
515
BUS
550
MEMORY
510
PROCESSOR(S)
520
NON-VOLATILE STORAGE
525
DATA STORAGE DEVICE
565
570
DISPLAY
575
ALPHANUMERIC INPUT DEVICE
580
CURSOR CONTROL
590
COMMUNICATIONS DEVICE

FIG. 5



600
INPUT SAMPLE REFLECTION 602
LIGHT ENGINE INTENSITIES 612
RGB COLOR VALUES 614
MLM ACTIVATION FUNCTIONS 616
OUTPUT TISSUE TYPE PROBABILITY VECTOR 620
MACHINE LEARNING MODEL 610
λ_1 λ_2 λ_3 λ_4 λ_5 λ_6 λ_m
R_1 R_2 R_3 R_4 R_5 R_6 R_n
I_1 I_2 I_3 I_4 I_5 I_6 I_n
R G B
P_A P_B P_C P_M

FIG. 6

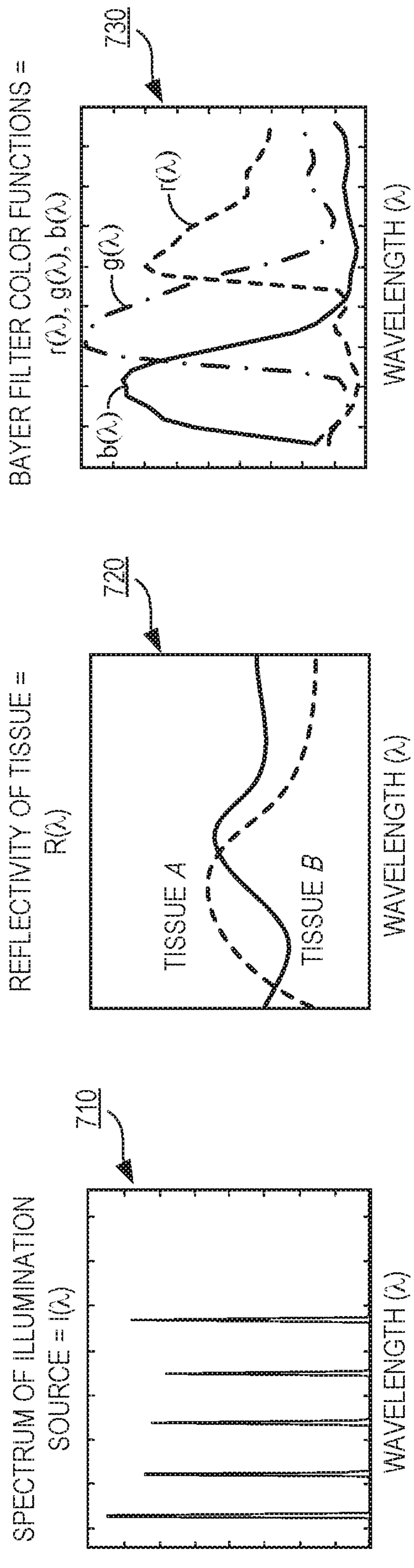

SPECTRUM OF ILLUMINATION SOURCE = I(λ)
710
WAVELENGTH (λ)
REFLECTIVITY OF TISSUE = R(λ)
720
TISSUE A
TISSUE B
WAVELENGTH (λ)
BAYER FILTER COLOR FUNCTIONS = r(λ), g(λ), b(λ)
730
b(λ)
g(λ)
r(λ)
WAVELENGTH (λ)

FIG. 7

SYSTEM AND METHOD FOR MULTICLASS CLASSIFICATION OF IMAGES USING A PROGRAMMABLE LIGHT SOURCE

CROSS-REFERENCE TO RELATED APPLICATION

This application is a continuation of U.S. application Ser. No. 15/445,121, filed Feb. 28, 2017, which is hereby incorporated by reference in its entirety.

TECHNICAL FIELD

This disclosure relates generally to digital imaging, and in particular but not exclusively, relates to classification of objects within image data.

BACKGROUND INFORMATION

When an image of an object is captured by a camera, a user may want to enhance the image by adjusting contrast of the image, accentuating certain features of the image, etc. when analyzing the object captured within the camera's field of view. For example, an image may be enhanced to distinguish between different mineral/soil compositions (e.g., in aerial or ground photography), to highlight blood flow (e.g., oxygenated and non-oxygenated blood), to perform emotion recognition and/or detection, to distinguish anatomy in surgery (e.g., to distinguish between benign and malignant tissue), etc. In medical imaging in particular, enhancing medical images, for example to distinguish between benign and malignant tissue, increases the safety and expands the reach of surgical interventions.

Specifically, during laparoscopic surgery, a surgeon inserts an endoscope into a small incision of a patient. The endoscope illuminates and captures images of a surgical area in real-time while the surgeon performs the surgery through the same or other incision, typically without physically viewing the area being operated on. A significant problem with such surgeries and the imaging used during such surgeries is that of low contrast between tissue(s) of interest and other tissue(s). For example, in a surgical procedure to excise cancerous tissue, the surgeon wants high contrast between the cancerous tissue and the healthy tissue so that the cancerous tissue can be removed while making no/minimal damage to surrounding healthy tissue. The problem is even more acute in surgery close to nerve tissue, where high contrast between adipose, cancerous, or other tissue and nerve tissue is needed to prevent inadvertent contact and/or removal of nerve tissue to prevent damage to the nervous system.

One solution to distinguishing between different tissue types during surgical procedures includes injecting fluorescent dyes into a patient where different dyes bind to different tissue types. When imaged with illumination from an excitation laser, the dye will fluoresce, and the desired tissue will appear much brighter in captured image data. To obtain high contrast between multiple tissues, a specific dye with a different excitation wavelength for each type of tissue is needed, a different excitation laser is needed for each tissue type, and a separate image for each tissue type is also needed. This approach for distinguishing between tissue types, however, typically requires the use of toxic dyes having specific fluorescence, which have not been approved by the Food and Drug Administration for use in humans, the development of which is a long, costly process. Furthermore, specific wavelength excitation lasers are needed and images must be captured for each dye/tissue combination. Thus, to obtain multiclass contrast between different types of tissues, the number of lasers and the number of images scales linearly with the number of tissue types to be differentiated.

BRIEF DESCRIPTION OF THE DRAWINGS

Non-limiting and non-exhaustive embodiments of the invention are described with reference to the following figures, wherein like reference numerals refer to like parts throughout the various views unless otherwise specified. The drawings are not necessarily to scale, emphasis instead being placed upon illustrating the principles being described.

FIG. **1** is a block diagram of an exemplary system architecture for multiclass classification of images using a programmable light source.

FIG. **2** is a block diagram of one embodiment of an endoscope and an image processing device having an endoscope controller.

FIG. **3** illustrates one embodiment of a process for using a machine learning model to perform multiclass classification of images using a programmable light source.

FIG. **4** is a flow chart illustrating one embodiment of a process for training a machine learning model for multiclass classification of images using a programmable light source.

FIG. **5** is one embodiment of a computer system that may be used with the present invention.

FIG. **6** illustrates one embodiment of a topography of a machine learning model for performing multiclass classification between different tissue types.

FIG. **7** illustrates one embodiment of exemplary inputs for determining recorded color pixel values.

DETAILED DESCRIPTION

Embodiments of an apparatus, system, and process for performing multiclass classification of objects within images using a programmable light source are described herein. In embodiments, a programmable light source illuminates a scene and a camera captures image data of the illuminated. In one embodiment, the programmable light source and the camera are integrated into an endoscope for use during, for example, laparoscopic surgery being performed by a medical professional.

In one embodiment, image data captured by the camera is provided to a trained machine learning model, such as a trained neural network, that analyzes color values of individual pixels of the image data to classify the individual pixels as belonging to one or more different classes. In embodiments, the different classes can be different classes of tissue imaged during a medical procedure. Furthermore, as discussed in greater detail below, the color values of the individual pixels are a function of the spectrum of illumination provided by the programmable light source, spectral reflectivities of tissue(s) being imaged, and color functions of a filter of the camera (e.g., Bayer filter color functions). The machine learning model may be trained prior to use using multispectral imaging and samples of classes of tissue to determine a spectrum of illumination of the programmable light source that optimally distinguishes between the classes of tissue. Furthermore, during use, the color values of the individual pixels are provided to the trained machine learning model to distinguish the classes of tissue on a per-pixel basis. Beneficially, hyperspectral quality imaging is used to train the machine learning model before use, but a much less bulky and much faster discrete imaging system is utilized during use to classify different tissue types based on color pixel values.

In embodiments, based on the classification of the pixels of the captured image data, the different classes of image data can be distinguished when rendered to a user, such as a surgeon performing a medical procedure. For example, a rendered image of a scene can include color overlays that visually distinguish between different tissue types. In embodiments, the surgeon can provide feedback, such as highlighting areas believed to be certain tissue types. This feedback data can be provided back to the machine learning model for training a machine learning model in real time and/or refinement of an existing machine learning model.

The description below refers to an endoscope with a camera and a programmable light source used during medical procedures for distinguishing between different classes of tissue. However, the presently described embodiments are not limited to endoscopes and/or medical procedures. Rather, the embodiments and techniques described herein are flexible, and can be used for performing multiclass classification for a wide class of imaging applications in which types of objects within image data are to be classified. However, for sake of clarity, the below description will be focused on multi-class tissue type classification.

Some portions of the detailed description that follow are presented in terms of algorithms and symbolic representations of operations on data bits within a computer memory. These algorithmic descriptions and representations are the means used by those skilled in the data processing arts to most effectively convey the substance of their work to others skilled in the art. An algorithm is here, and generally, conceived to be a self-consistent sequence of steps leading to a desired result. The steps are those requiring physical manipulations of physical quantities. Usually, though not necessarily, these quantities take the form of electrical or magnetic signals capable of being stored, transferred, combined, compared, and otherwise manipulated. It has proven convenient at times, principally for reasons of common usage, to refer to these signals as bits, values, elements, symbols, characters, terms, numbers, or the like.

It should be borne in mind, however, that all of these and similar terms are to be associated with the appropriate physical quantities and are merely convenient labels applied to these quantities. Unless specifically stated otherwise as apparent from the following discussion, it is appreciated that throughout the description, discussions utilizing terms such as "applying", "illuminating", "capturing", "analyzing", "rendering", "determining", "identifying", "generating", "measuring", "using", "receiving", "providing", or the like, refer to the actions and processes of a computer system, or similar electronic computing device, that manipulates and transforms data represented as physical (e.g., electronic) quantities within the computer system's registers and memories into other data similarly represented as physical quantities within the computer system memories or registers or other such information storage, transmission or display devices.

The present invention also relates to an apparatus for performing the operations herein. This apparatus may be specially constructed for the required purposes, or it may comprise a general purpose computer selectively activated or reconfigured by a computer program stored in the computer. Such a computer program may be stored in a computer readable storage medium, such as, but not limited to, any type of disk including floppy disks, optical disks, CD-ROMs, and magnetic-optical disks, read-only memories (ROMs), random access memories (RAMs), EPROMs, EEPROMs, magnetic or optical cards, or any type of media suitable for storing electronic instructions.

The algorithms and displays presented herein are not inherently related to any particular computer or other apparatus. Various general purpose systems may be used with programs in accordance with the teachings herein, or it may prove convenient to construct a more specialized apparatus to perform the required method steps. The required structure for a variety of these systems will appear from the description below. In addition, the present invention is not described with reference to any particular programming language. It will be appreciated that a variety of programming languages may be used to implement the teachings of the invention as described herein.

FIG. **1** is a block diagram of an exemplary system architecture for multiclass classification of images using a programmable light source. In one embodiment, the system **100** includes an endoscope **110** communicably coupled with an image processing device **120**. In embodiments, endoscope **110** may be coupled via physical connection (e.g., wired connection), via a wireless connection (e.g., wireless network, personal area network, near field communication, etc.), or other type of communications link. Furthermore, the image processing device **120** may be communicably coupled with a display **130** and an imaging data store **140**, over any of the communications links discussed herein.

Endoscope **110** is responsible for capturing images of a scene with camera **114**. Camera **114** may include a lens **116** and an image sensor **118**. The lens **116** of camera **114** allows light to pass from outside of endoscope **110** (e.g., a scene) to the image sensor **118** of camera **114**. In one embodiment, the image sensor is a Bayer image sensor that includes a color arrangement of red, green, and blue color filters on a pixel array of the image sensor **118**. Thus, the image sensor **118** captures the light filtered through the color filters on a grid of photosensitive pixels and conveys red, green, or blue image information for each pixel to image processing device **120**.

Image processing device **120** is a computer processing system, such as a desktop computer, laptop computer, tablet computer, mobile telephone, or purpose build computing device, which includes a processor, memory, communication interfaces, and other components typically found in computer processing systems. One embodiment of a computing processing system is discussed in greater detail below in FIG. **5**. In one embodiment, image processing device **120** receives image data (e.g., red, green, or blue data for each pixel of image sensor **118**) captured by camera **114** of endoscope **110**, which can be processed and displayed on display **130** and/or stored in an imaging data store **140**. For example, display **130** may render captured image data to a doctor, nurse, or other medical professional that is analyzing image data captured by endoscope **110**. Furthermore, imaging data store **140** may store captured image data for later analysis by a health care professional, such as storing image data captured during a medical procedure for further training a machine learning model used by endoscope controller **125**, storing image data to a patient's electronic medical records, etc.

In one embodiment, endoscope **110** utilizes programmable light source(s) **112** to illuminate a scene during a medical procedure. As illustrated in FIG. **1**, different types of tissue **180** (e.g., tissue A and tissue B) are imaged during a medical procedure using endoscope **110**. In one embodiment, the programmable light source(s) **112** include one or more discrete lasers that are configurable by endoscope controller **125** at selected wavelengths and power levels when illuminating the scene including the different tissues **180**. Furthermore, the power of each laser can be independently modulated as determined by endoscope controller **125** thereby creating the independently programmable light source(s).

In one embodiment, camera **114** captures the light generated by the programmable light source(s) **112** and reflected from the different tissues **180** in the scene using image sensor **118**. In one embodiment, image sensor **118** includes a Bayer filter having a color filter array arranged over a grid of photosensors. Thus, every pixel of the camera's **114** sensor **118** captures a function of the red, green, or blue light reflected from a scene, such as each photosensor recording a different weighted integral of the incident spectrum (e.g., Red=∫(I(λ)R(λ)r(λ)d, Green=∫(I(λ)R(λ)g(λ)d, and Blue=∫(I(λ)R(λ)b(λ)d). That is, the recorded red, green, or blue values at each pixel are a function of the spectrum of the programmable light source(s) **710** (e.g. I(λ)), the reflectivity of the tissue being imaged at each pixel **720** (e.g., R(λ)), and the Bayer filter color functions for the associated pixel filter color (e.g., one of r(λ), g(λ), or b(λ)), as illustrated in FIG. **7**. The recorded value is a color value at each pixel, which is a Bayer filter color function **730** value of the wavelength of the reflected light. As will be discussed in greater detail below, the powers applied to the discrete programmable light source(s) **112** by endoscope controller **125** are optimized such that the data captured by color pixels for red, green, and blue pixels of the filter **118** optimally capture differences in reflectivity of different tissue types. Endoscope controller **125** utilizes a trained machine learning model, such as a trained neural network, to analyze the captured red, green, or blue color values at each pixel and classify each pixel as belonging to a specific tissue type or an unknown tissue type. For example, based on differences in reflectivities of tissue A and tissue B **180**, endoscope controller's **125** machine learning model based analysis of the captured color data enables endoscope controller to classify each pixel as belonging to tissue of type A, type B, or neither, based on a probabilistic analysis performed by the trained machine learning model that a pixel belongs to one of the classes of tissue.

In one embodiment, endoscope controller **125** generates visualization **182** of the tissue types in real time during a medical procedure based on the determined classification probabilities, which is rendered on display **130**. In one embodiment, the visualization **182** of each tissue type during surgery includes a color overlay selectively displayed over each pixel of captured image data on display **130**. The color overlay image can include a different color for each type of tissue rendered in real time over the captured image data for a surgeon or other medical professional. That is, for each classifiable tissue type, a different color is assigned, and a probability mapping of each tissue type to pixels of a captured image can govern the opacity of the color over the image to, in embodiments, distinguish between different tissue types and provide an indication of the likely accuracy of the determined classification. Thus, different color overlays are created for each tissue type at each pixel of captured image data to differentiate regions of tissue type, increase contrast between tissue types, warn a medical professional using endoscope of the location of specific types of tissue, etc. These color overlays can be rendered to create a single visualization **182** where different types of tissue are conspicuously differentiated based on the boundaries of the color overlays. However, each color overlay can be toggled through by a surgeon or medical professional in real time as image data is captured by endoscope **110**.

FIG. **2** is a block diagram of one embodiment **200** of an endoscope **210** and an image processing device **250**. Endoscope **210** and an image processing device **250** provide additional details for the endoscope **110** and image processing device **120** discussed above. Furthermore, although not shown, image processing device may be communicably coupled to a display and/or an imaging data store as discussed above.

In one embodiment, the image processing device **250** includes endoscope controller **252** having an endoscope interface **255**, a light engine controller **260**, a machine learning model analysis engine **265**, a display rendering engine **290**, an optional machine learning model training engine **270**, and a store of machine learning models **280**. As discussed above in FIG. **1**, the endoscope **210** includes one or more programmable light source(s) **212** (e.g., individually controllable lasers) and a camera **214** having a lens **216** and an image filter **218** (e.g., a Bayer color filter over an array of photosensors/pixels). In one embodiment, the endoscope **210** communicates with image processing device **250** via endoscope interface **255** over a wired or wireless communications link, as discussed above in FIG. **1**.

The image processing device **250**, in embodiments, can be implemented in a computing device, such as a desktop computer, laptop computer, tablet computer, purpose built computing appliance, video game console, mobile telephone, as well as other computing devices. Endoscope interface **255** is responsible for communicably coupling the endoscope controller **252** of image processing device **250** with endoscope **210** to enable endoscope controller **260** the ability to control the programmable light source(s) **212** of endoscope **210**, as well as to receive color pixel data captured by camera **214** of endoscope **210**.

In one embodiment, light engine controller **260** is responsible for configuring the programmable light source(s) **212** of endoscope. In one embodiment, programmable light source(s) **212** include individually configurable light sources that illuminate a scene (e.g., discrete wavelength laser light sources with modulatable power levels). In one embodiment, light engine controller **260** configures each of the programmable light source(s) **212** to illuminate the scene at a corresponding power level. In one embodiment, the power level for each of the programmable light source(s) **212** is determined by light engine controller **260** from a trained machine learning model (MLM) used by MLM analysis engine **265** when performing multi-class tissue type classification. A machine learning model, which is trained according to the discussion below, is accessed by endoscope controller **125** to determine power weighting values corresponding to power weighting functions found by, for example neural network optimization, to program the intensities/power levels applied to the one or more programmable light source(s) **212** by light engine controller **260**.

Camera **214** captures an image of the scene as illuminated by programmable light source(s) **212**. More specifically, the light reflected from one or more types of tissue in the scene passes through lens **216** and onto sensor **218**. Sensor **218**, in one embodiment, is a Bayer color filter that has a matrix of red, green, and blue color pixels. The color values captured by each pixel are provided to endoscope controller **252** for MLM analysis engine **265** to analyze using a selected machine learning model corresponding to the machine learning model used to configure the programmable light source(s) **212**.

Prior to use of a machine learning model by MLM analysis engine **265**, endoscope controller may obtain one or more MLM models trained by a remote system using the techniques discussed herein, and store them in MLM data store **280**. Additionally, or alternatively, MLM training engine **270** may perform a machine learning process to locally train one or more machine learning models for performing multi-class tissue type classification or further refine an already trained MLM. In embodiments, each machine learning model utilized by MLM analysis engine **265** enables differentiation between a set of two or more types of tissue.

In one embodiment, where endoscope controller **252** locally performs machine learning model training, MLM training engine **270** is communicably coupled with a hyperspectral imager (not shown) via hyperspectral imager (HSI) interface **275**. In this embodiment, the hyperspectral imager is responsible for supply training data to the MLM training engine **270** in the form of measured reflectance of one or more tissue samples in response to a plurality of different discrete illumination wavelengths. In one embodiment, MLM training engine **265** trains a machine learning model, such as the neural network illustrated in FIG. **6**, for differentiating tissue types of interest. For example, the machine learning model of FIG. **6** can differentiate, after training, between a plurality of different tissue types, such as tissue types A though M.

In one embodiment, to train the machine learning model of FIG. **6**, tissue samples of the tissue types of interest, such as tissue types A through M, are imaged with a hyperspectral imager (not shown). Hyperspectral imaging yields reflectance for a plurality of discrete wavelengths for every pixel of image data captured by the hyperspectral imager. Since the tissues being imaged by the hyperspectral image are of known type (e.g., one or more samples of each of tissue types A through M), the deep neural network machine learning model **610** can be iteratively trained by MLM analysis engine **265** using any of the standard machine learning techniques from the spectral reflectivity inputs of each pixel (e.g., red, green, and blue pixels), and the desired output being (e.g., a vector of probabilities having a one for the known tissue type and a zero for all other tissue types). As illustrated in FIG. **6**, one embodiment of a deep neural network machine learning model **610** includes a plurality of layers of weighted activation functions, where each weighted activation function receives an input from a previous layer and computes an output that is provided to activation function(s) of other layers. The interconnected nodes, and their weighted computations, can include linear activation functions, non-linear activation functions, or a combination of both based on the classification to be performed and the results of the classification process (e.g., whether linear techniques yield expected results, or whether non-linear or combined techniques yield expected results). In one embodiment, the deep neural network machine learning model **610** includes a light engine intensities **612** layer of activation functions, an RGB color value **614** layer of activation functions and zero or more zero or more additional layers of MLM activation functions. The reflection input **602**, light engine intensities **212**, and RGB color values **614** essentially model the physics surrounding the illumination of the tissue sample and the resulting reflection, with the remaining layers of activation functions enabling statistical prediction from the modeled physics of the input and first two machine learning model layers. That is, the training input and first two layers of the deep neural network machine learning model **610** calculate the values of red, green, and blue from the spectral reflectivities **614**, while the remaining layers **616** of the neural network take the red, green, and blue intensity values, as well as the weight of all nodes after the first three layers, and transform them into the tissue type probability vector **620**. The programmable light intensities as well as the weightings of all nodes after the first two layers are therefore iteratively optimized by the machine learning process in order to minimize training error for the samples of known tissue type.

During training, responsive to the input sample reflection data **602** and based on a machine learning process, the light engine intensities **612** layer of activation functions iteratively refine weightings applied to the wavelengths of the illumination source (e.g., programmable light source(s) **212**), iteratively refine the RGB color value **614** activation functions (e.g., computed red, green, or blue color values as a function of the light engine intensities **612** and the input sample reflection **602**), and iteratively refine the zero or more additional layers of MLM activation functions to minimize training error of the expected probability vector associated with a tissue of known type. That is, the machine learning process used by MLM analysis engine **265** to train the machine learning model iteratively adjusts the activation functions and weightings of each layer of activation function at each node of the neural network machine learning model **610** with each training iteration to minimize the error when obtaining a desired output having a probability of 1 for the actual tissue type of the sample being imaged (e.g., the known tissue type), and a probability of 0 for all the other tissue types (e.g., other classifications not being imaged).

In embodiments, machine learning models, such as neural network machine learning model **610**, are scalable to any number of categories/types of tissue. After a sufficient number of tissue samples have been imaged at a sufficient number of wavelengths by a hyperspectral imager, and MLM training engine **270** has performed a corresponding number of iterative refinements of the deep neural network machine learning model **610**, the resulting model can be stored in MLM data store for later use by MLM analysis engine **265**.

In embodiments, however, the deep neural network machine learning model **610** may alternatively be trained by a remote system (not shown) and not MLM training engine **270**. In this embodiment, the remote system provides endoscope controller **252** with the trained machine learning model for user during medical procedures where distinguishing between tissue types in the model are desired. In embodiments, the remote system can provide a set of procedure specific trained machine learning models, a set of different multi-class classifiers for distinguishing between different groupings of tissue type, etc. for storage in MLM data store **280**. As another example, MLM analysis engine **265** can request and receive a specific multi-class tissue type classification model on a procedure-by-procedure basis.

In another embodiment, MLM training engine **270** can receive training data from endoscope **210**. In embodiments, this training data can be received in response to the training of a new machine learning model or in response to a refinement of an existing machine learning model. In this embodiment, MLM training engine **270** initially receives highlighted, annotated, or otherwise differentiated areas of image data captured by endoscope **210** (e.g., a surgeon's real time annotations of image data during a medical procedure). For example, a cursor or touch input device can provide input for a display system coupled with an image processing device, which is displaying real-time image data of a scene captured by endoscope **210**. In embodiments, the differentiated areas are received in real-time with annotations for each area and the corresponding believed tissue type. MLM training engine **270** instructs light engine controller **260** to individually iterate through each of the discrete programmable light source(s) **212**, illuminating the scene with each light source one at a time and storing the corresponding image in a memory accessible to MLM training engine **270**. The set of images corresponding to the different light sources yields partial spectral reflectivities for each pixel of captured image data. In one embodiment, the partial spectral reflectivities are fed into the machine learning model for iteratively training a machine learning model, such as a deep neural network machine learning model, as discussed above. In one embodiment, a new machine learning model may be trained using the partial spectral reflectivities. In another embodiment, an existing trained machine learning model (e.g. a model trained using hyperspectral imaging), may be refined using real-time surgical annotations.

After training a machine learning model using one of the techniques discussed above, or after acquiring a trained machine learning model, endoscope controller **252** utilizes the trained machine learning model for performing real time multi-class tissue type classification during medical procedures, and generating appropriate visualizations. In one embodiment, MLM analysis engine **265** performs a pixel wise machine learning model analysis in order to classify each pixel as belonging to one of a plurality of different classes of tissue types. In embodiments, color information captured by each pixel is fed into an appropriate intermediate layer of the machine learning model being used by MLM analysis engine **265** (e.g., layer **614** of machine learning model **610**). The intermediate layer of the machine learning model takes as input the color value of a Bayer color filter pixel, performs a series of machine learning model computations using the color value as an input, and outputs a probability vector with probabilities that the pixel belongs to one of the various potential classes of tissue. That is, during a medical procedure, the recorded red, green, or blue color value for each pixel of filter **218** is fed by MLM analysis engine **265** into the appropriate intermediate layer of a trained machine learning model (e.g., the RGB color value layer **614** of the trained deep neural network **610** illustrated in FIG. **6**). The machine learning model **610** then outputs a probability vector to MLM analysis engine **265** that provides a probability that imaged tissue at the pixel is one of the different classes of tissue, for each pixel of the image. The probability vectors for the pixels of captured image data enable MLM analysis engine **265** to classify each pixel of an image as belonging to one of the multiple classifications (e.g., belonging to tissue of Type A or Type B in FIG. **1**, or as belonging to any of tissue types A through M in FIG. **6**). Although full spectral information can be used to train the machine learning model when using a hyperspectral imager, as discussed in greater detail above, the full spectral information is not utilized by MLM analysis engine **265** when using the trained machine learning model to classify different tissue types in image data. Rather, that information is encoded into the one or more programmable light source(s) **112** using the machine learning model as trained. This physical preprocessing provides a surgeon or other medical professional utilizing endoscope **210** and image processing device **250** the benefit of hyperspectral information (e.g., used to train the machine learning model), without needing a slow, bulky, and costly hyperspectral imager in endoscope **210** (e.g., applying the machine learning model using color information).

In embodiments, MLM analysis engine **265** performs machine learning model based analysis of color information captured for each pixel of image data in real time as image data is captured by camera **214**, and provides the analysis results to display rendering engine **290**. Display rendering engine **290** receives the analysis results, including the probability vectors for each pixel of image data. In one embodiment, the probability vectors are utilized to generate one or more visualization(s) that enhance captured image data rendered on a display device (not shown) coupled with image processing device. The visualization(s) can include enhancing contrast between two regions having tissues of different types (e.g., enhancing contrast between nerve and cancer tissue), generating color overlays for different classes of tissue types (e.g., color overlays over fat, muscle, and intestinal tissue), generating a notice for unknown zones of tissue type (e.g., a zone for which a probability vector is not able to predict any tissue type of interest within a threshold degree of accuracy), generating warnings when a medical tool encroaches on a zone having a specific tissue type (e.g., when a medical tool approaches a threshold distance to nerve tissue), etc. The visualizations are generated in real time or near real time as image data is captured by camera **214**. Thus, the visualizations provide valuable real-time feedback and tissue type differentiation to medical professionals during a medical procedure.

FIG. **3** illustrates one embodiment of a process **300** for using a machine learning model to perform multiclass classification of images using a programmable light source. The process is performed by processing logic that may comprise hardware (circuitry, dedicated logic, etc.), software (such as is run on a general purpose computer system or a dedicated machine), firmware, or a combination. In one embodiment, the process is performed by an endoscope and an image processing device (e.g., endoscope **110** or **210**, and image processing device **120** or **250**).

Referring to FIG. **3**, processing logic begins by accessing a trained multi-class tissue type classification machine learning model (processing block **302**). As discussed herein, one or more trained machine learning models for differentiating between tissue types based on color information may be obtained from a remote system and/or trained by processing logic. Each machine learning model may be a trained neural network that differentiates between different sets of tissue types, and may be used for different or select procedures. For example, machine learning models relevant to abdominal procedures, cardiac procedures, or other types of procedures can provide for tissue type classification for the types of tissue likely to be encountered during the respective procedures. Furthermore, processing logic can access one of the machine learning models based on user selection prior to usage of an endoscope in the associated procedure.

Processing logic configures one or more programmable light source(s) of an imaging system based on a weighting of light source(s) in the machine learning model (processing block **304**). In one embodiment, the weightings corresponding with weighting extracted from the selected machine learning model. For example, the weightings can correspond with weightings applied to light engine intensities as the result of the training of the selected machine learning model (e.g., weightings applied to activation functions **612**). In embodiments, processing logic powers each light programmable light source according to its respective weighting so that the combined weightings applied to the programmable light sources match the weightings extracted from the machine learning model.

Processing logic illuminates a scene with the configured light source(s) (processing block **306**) Processing logic then captures an image of the scene including one or more types of tissue depicted in the image data (processing block **308**). As discussed herein, the light source illuminates the scene by shining one or more laser lights at discrete illumination wavelengths and configured power levels. An image sensor, such as Bayer color filter having an array of photosensors with a color grid overlay, then captures the light reflected from the tissue(s) in the scene.

For each pixel of captured image data, the pixels corresponding to pixels of an image filter of a camera, processing logic inputs color information from the captured image data into an intermediate layer of the machine learning model to classify that pixel as belonging to different tissue types (processing block **310**). In one embodiment, the intermediate layer is an intermediate layer of a trained neural network machine learning model that performs activation function calculations on pixel color value, which are in turn used by the remaining layers of the trained neural network machine learning model to compute a probability vector associated with that pixel. As discussed herein, the probability vector includes probabilities that the pixel belongs to each potential type of tissue. When the probability exceeds a threshold value (e.g., 85%, 90%, 99%, etc.), processing logic concludes that the pixel of image data has captured image data of the corresponding tissue type. This can be repeated for each pixel so that the entire image, or a subset of an image, can be classified according to tissue type captured therein.

Processing logic utilizes the classifications to render a visualization of the captured image data including a visual differentiation between tissues determined to belong to different types (processing block **312**). In embodiments, the differentiation between tissue types in the rendered visualization can include contrast enhancement between tissue types of interest. In another embodiment, color overlays may be generated for each tissue type of interest, with opacity of each color overlay adjusted to account for the computed probability (e.g., the higher the probability, the more opaque a region is rendered in the visualization). In embodiments, the color overlays and/or contrast enhancements can be selectively activated and/or deactivated by the medical professional(s) performing the procedure. Furthermore, different visualizations can be stepped through, such as by turning on/off individual color overlays, enhancing contrast of selected types of tissue, etc. Each of the visualizations and the control of the visualization provide a medical professional improved imaging of a scene, which is valuable since the medical professionals typically perform medical procedures with endoscopes without actually seeing the scene.

FIG. **4** is a flow chart illustrating one embodiment of a process **400** for training a machine learning model for multiclass classification of images using a programmable light source. The process is performed by processing logic that may comprise hardware (circuitry, dedicated logic, etc.), software (such as is run on a general purpose computer system or a dedicated machine), firmware, or a combination. In one embodiment, the process is performed by an endoscope and an image processing device (e.g., endoscope **110** or **210**, and image processing device **120** or **250**), a remote processing system, or a combination of systems, as discussed herein.

Referring to FIG. **4**, processing logic begins by initiating training of a machine learning model (MLM) for performing multi-class tissue type classification (processing block **402**). In embodiments, the training is initiated before a medical procedure is performed. The training can include training a new model using hyperspectral imaging to image a plurality of tissue samples at a plurality of illumination wavelengths. The training can also include training a new model using the illumination sources of an endoscope, and tissue type selects made by a medical professional. Additionally, the training can include a combination of both training techniques where an existing hyperspectrally trained machine learning model is further refined with real-time tissue type selection.

Processing logic measures a spectral reflectance of a tissue sample of a tissue type of interest at one of a plurality of discrete illumination wavelengths to determine reflectance of the tissue sample as a function of that illumination wavelength (processing block **404**). In one embodiment, the spectral reflectance corresponds with measurements taken for a plurality of discrete illumination wavelengths generated by a hyperspectral imager. In another embodiment, the spectral reflectance corresponds with partial spectral reflectivity measurements taken for each programmable light source of an endoscope.

Processing logic inputs the measured spectral reflectance for the tissue type into a MLM training process for the machine learning model (processing block **406**). As discussed herein, the input is used to iteratively train the machine learning model by inputting the measured spectral reflectance values into the machine learning model for a known tissue type. The training methods are discussed in greater detail above.

Processing logic then determines if there are more wavelengths for which spectral reflectance data is desired (processing block **408**) and if there are more tissue type samples of the same and/or different tissue type (processing block **410**). If either of these processing blocks is true, the process returns to processing block **404** to measure spectral reflectance and further train the machine learning model. In embodiments, the machine learning model is iteratively trained using a plurality of different wavelengths of illumination of each tissue sample and a plurality of different samples of the same and different type. However, when there is no more training data to be obtained and input into the machine learning model training process, the process ends.

FIG. **5** is one embodiment of a computer system that may be used with the present invention. The computer system may provide the functionality of the image processing systems discussed above. Furthermore, it will be apparent to those of ordinary skill in the art, however, that other alternative systems of various system architectures may also be used.

The computer system illustrated in FIG. **5** includes a bus or other internal communication means **515** for communicating information, and a one or more processor(s) **510** coupled to the bus **515** for processing information. The system further comprises a random access memory (RAM) or other volatile storage device **550** (referred to as memory), coupled to bus **515** for storing information and instructions to be executed by processor(s) **510**. Memory **550** also may be used for storing temporary variables or other intermediate information during execution of instructions by processor **510**. The system also comprises a read only memory (ROM) and/or static storage device **520** coupled to bus **515** for storing static information and instructions for processor **510**, and a data storage device **525** such as a magnetic disk or optical disk and its corresponding disk drive. Data storage device **525** is coupled to bus **515** for storing information and instructions.

The system may further be coupled to a display device **570**, such as a light emitting diode (LED) display, a liquid crystal display (LCD), etc., coupled to bus **515** through bus

565 for displaying information to a computer user, such as a medical professional utilizing the image processing system during a medical procedure. An alphanumeric input device **575**, including alphanumeric and other keys, may also be coupled to bus **515** through bus **565** for communicating information and command selections to processor **510**. An additional user input device is cursor control device **580**, such as a mouse, a trackball, stylus, or cursor direction keys coupled to bus **515** through bus **565** for communicating direction information and command selections to processor **510**, and for controlling cursor movement on display device **570**.

Another device, which may optionally be coupled to computer system **500**, is a communication device **590** for accessing other nodes of a distributed system via a network. The communication device **590** may include any of a number of commercially available networking peripheral devices such as those used for coupling to an Ethernet, token ring, Internet, or wide area network. The communication device **590** may further be a null-modem connection, or any other mechanism that provides connectivity between the computer system **500** and the outside world. Note that any or all of the components of this system illustrated in FIG. **5** and associated hardware may be used in various embodiments of the present invention.

It will be appreciated by those of ordinary skill in the art that any configuration of the system may be used for various purposes according to the particular implementation. The control logic or software implementing the present invention can be stored in memory **550**, data storage device **525**, or other storage medium locally or remotely accessible to processor(s) **510**.

It will be apparent to those of ordinary skill in the art that the systems, methods, and processes described herein can be implemented as software stored in memory **550** or read only memory **520** and executed by processor(s) **510**. This control logic or software may also be resident on an article of manufacture comprising a computer readable medium having computer readable program code embodied therein and being readable by the data storage device **525** and for causing the processor(s) **510** to operate in accordance with the methods and teachings herein.

The present invention may also be embodied in a handheld or portable device, such as a tablet computer system, laptop computer system, smartphone, smart glasses, etc., containing a subset of the computer hardware components described above. For example, the handheld device may be configured to contain only the bus **515**, the processor(s) **510**, and memory **550** and/or **525**. The handheld or portable device may also be configured to include a set of buttons or input signaling components with which a user may select from a set of available options. The handheld or portable device may also be configured to include an output apparatus such as a liquid crystal display (LCD) for displaying information to a user of the handheld or portable device. Conventional methods may be used to implement such a handheld or portable device. The implementation of the present invention for such a device would be apparent to one of ordinary skill in the art given the disclosure of the present invention as provided herein.

The present invention may also be embodied in a special purpose appliance including a subset of the computer hardware components described above. For example, the appliance may include a processor(s) **510**, a data storage device **525**, a bus **515**, and memory **550**, and only rudimentary communications mechanisms, such as a small touch-screen that permits the user to communicate in a basic manner with the device. In general, the more special-purpose the device is, the fewer of the elements need be present for the device to function.

The processes explained above are described in terms of computer software and hardware. The techniques described may constitute machine-executable instructions embodied within a tangible or non-transitory machine (e.g., computer) readable storage medium, that when executed by a machine will cause the machine to perform the operations described. Additionally, the processes may be embodied within hardware, such as an application specific integrated circuit ("ASIC") or otherwise.

A tangible machine-readable storage medium includes any mechanism that provides (i.e., stores) information in a non-transitory form accessible by a machine (e.g., a computer, network device, personal digital assistant, any device with a set of one or more processors, etc.). For example, a machine-readable storage medium includes recordable/non-recordable media (e.g., read only memory (ROM), random access memory (RAM), magnetic disk storage media, optical storage media, flash memory devices, etc.).

The above description of illustrated embodiments of the invention, including what is described in the Abstract, is not intended to be exhaustive or to limit the invention to the precise forms disclosed. While specific embodiments of, and examples for, the invention are described herein for illustrative purposes, various modifications are possible within the scope of the invention, as those skilled in the relevant art will recognize.

These modifications can be made to the invention in light of the above detailed description. The terms used in the following claims should not be construed to limit the invention to the specific embodiments disclosed in the specification. Rather, the scope of the invention is to be determined entirely by the following claims, which are to be construed in accordance with established doctrines of claim interpretation.

What is claimed is:

1. A method of training a machine learning model to identify one or more types of tissue included in different tissue types, the method comprising:

illuminating one or more tissue samples for each of the one or more types of tissue;

measuring spectral reflectivities of the one or more tissue samples at a plurality of discrete illumination wavelengths to determine a reflectance of the one or more tissue samples as a function of illumination wavelength;

iteratively training the machine learning model, using the spectral reflectivities as inputs to the machine learning model, for probabilistic identification of a tissue type based on color image data from a camera, wherein the machine learning model includes an artificial neural network having a plurality of layers of weighted transfer functions, including:

a first layer that multiples the inputted spectral reflectivities by a spectrum of an illumination source;

a second layer that multiplies values computed in the first layer one or more color functions of the camera; and

at least one additional layer that receives the multiplied values computed by the second layer, and wherein an output of the machine learning model is a vector of probabilities corresponding to the probabilistic identification of the tissue type.

2. The method of claim **1**, wherein the spectral reflectivities are measured with a hyperspectral imager.

3. The method of claim 1, wherein the one or more color functions of the camera include a red color function, a blue color function, and a green color function that each correspond to a respective filter of the camera, wherein the camera is not a hyperspectral imager, and wherein the training of the machine learning model with the spectral reflectivities configures weightings of at least the first layer to correspond to a configuration of one or more programmable light sources for the probabilistic identification of the tissue type from the color image data provided by the camera.

4. The method of claim 3, wherein the configuration corresponds to intensity or power of the one or more programmable light sources.

5. The method of claim 3, wherein the configuration provided by the machine learning model captures differences in spectral reflectivity between the different tissues types that are within at least one of the red color function, the blue color function, or the green color function of the respective filter of the camera.

6. The method of claim 3, further comprising refining the machine learning model with additional training, including:

applying the configuration to the one or more programmable light sources based on at least the weightings of the first layer of the machine learning model to illuminate a scene;

receiving real-time user annotations of the image data of the scene that classify portions of the image data depicting the one or more types of tissue as belonging to one of the different tissue types;

iteratively illuminate the scene with each of the one or more programmable light sources and capturing images associated with each illuminated version of the scene with the camera, wherein the captured images provide partial spectral reflectivities of the classified portions; and

providing the partial spectral reflectivities as inputs corresponding to the input spectral reflectivities to iteratively train the machine learning model to provide the probabilistic identification of the tissue type from the color image data.

7. The method of claim 1, wherein the training of the machine learning model is specific to a type of procedure.

8. The method of claim 1, wherein the inputted spectral reflectivities, the first layer, and the second layer collectively calculate values of red, green, and blue intensity values associated with the one or more color functions, and wherein subsequent layers of the machine learning model, including the at least one additional layer, take the red, green, and blue intensity values and transform them into the vector of probabilities based, at least in part, on weights of all nodes included in the subsequent layers.

9. The method of claim 1, wherein the second layer is disposed between the first layer and the at least one additional layer of the machine learning model.

10. The method of claim 1, wherein the training of the machine learning model iteratively adjusts weighting for nodes included in each of the plurality of layers of the weighted transfer function for each training iteration.

11. A non-transitory machine readable storage medium having instructions stored thereon, which when executed by a processing system, cause the processing system to perform a method of training a machine learning model to identify one or more types of tissue included in different tissue types, comprising:

illuminating one or more tissue samples for each of the one or more types of tissue;

measuring spectral reflectivities of the one or more tissue samples at a plurality of discrete illumination wavelengths to determine a reflectance of the one or more tissue samples as a function of illumination wavelength;

iteratively training the machine learning model, using the spectral reflectivities as inputs to the machine learning model, for probabilistic identification of a tissue type based on color image data from a camera, wherein the machine learning model includes an artificial neural network having a plurality of layers of weighted transfer functions, including:

a first layer that multiples the inputted spectral reflectivities by a spectrum of an illumination source;

a second layer that multiplies values computed in the first layer one or more color functions of the camera; and

at least one additional layer that receives the multiplied values computed by the second layer, and wherein an output of the machine learning model is a vector of probabilities corresponding to the probabilistic identification of the tissue type.

12. The non-transitory machine readable storage medium of claim 11, wherein measuring the spectral reflectivities is performed with a hyperspectral imager.

13. The non-transitory machine readable storage medium of claim 11, wherein the one or more color functions of the camera include a red color function, a blue color function, and a green color function that each correspond to a respective filter of the camera that is not a hyperspectral imager, and wherein the training of the machine learning model with the spectral reflectivities configures weightings of at least the first layer to correspond to a configuration of one or more programmable light sources for the probabilistic identification of the tissue type from the color image data provided by the camera.

14. The non-transitory machine readable storage medium of claim 13, wherein the configuration corresponds to intensity or power of the one or more programmable light sources.

15. The non-transitory machine readable storage medium of claim 13, wherein the configuration provided by the machine learning model captures differences in spectral reflectivity between the different tissues types that are within at least one of the red color function, the blue color function, or the green color function of the respective filter of the camera.

16. The non-transitory machine readable storage medium of claim 13, further comprising refining the machine learning model with additional training, including:

applying the configuration to the one or more programmable light sources based on at least the weightings of the first layer of the machine learning model to illuminate a scene;

receiving real-time user annotations of the image data of the scene that classify portions of the image data depicting the one or more types of tissue as belonging to one of the different tissue types;

iteratively illuminate the scene with each of the one or more programmable light sources and capturing images associated with each illuminated version of the scene with the camera, wherein the captured images provide partial spectral reflectivities of the classified portions; and

providing the partial spectral reflectivities as inputs corresponding to the input spectral reflectivities to iteratively train the machine learning model to provide the probabilistic identification of the tissue type from the color image data.

17. The non-transitory machine readable storage medium of claim **11**, wherein the training of the machine learning model is specific to a type of procedure.

18. The non-transitory machine readable storage medium of claim **11**, wherein the inputted spectral reflectivities, the first layer, and the second layer collectively calculate values of red, green, and blue intensity values associated with the one or more color functions, and wherein subsequent layers of the machine learning model, including the at least one additional layer, take the red, green, and blue intensity values and transform them into the vector of probabilities based, at least in part, on weights of all nodes included in the subsequent layers.

19. The non-transitory machine readable storage medium of claim **11**, wherein the second layer is disposed between the first layer and the at least one additional layer of the machine learning model.

20. The non-transitory machine readable storage medium of claim **11**, wherein the training of the machine learning model iteratively adjusts weighting for nodes included in each of the plurality of layers of the weighted transfer function for each training iteration.

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